Harnessing Soft Information to Promote Financial Inclusion: Native CDFI Lending and Business Loan Delinquency*

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Abstract

Native Community Development Financial Institutions (NCDFIs) promote financial inclusion in financially underserved Native communities by adopting innovative lending strategies, including designing own soft-information-based measures of borrower risk. Drawing on business loan data from one prominent NCDFI, a nonprofit loan fund, we examine whether such NCDFI-generated measures help explain NCDFI loan performance. We show that the hazard of loan delinquency is robustly negatively associated with one soft-information-based borrower risk measure, the character score, but does not vary with another one, commitment to business. Both NCDFI-created measures exhibit important interactions with credit score, a conventional credit-bureau-produced hard-information-based metric. Our findings offer insight into which aspects of NCDFI lending practices can be helpful in improving financial viability of NCDFIs and thus in fostering financial inclusion of NCDFI clients. More broadly, our study offers evidence in support of NCDFI underwriting practices and relationship-based lending operations.

Keywords: Native CDFIs, financial inclusion, soft information, business lending, delinquency

JEL Classifications: G21, G11, J15, O16, P43

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Introduction

Native communities in the U.S. have been persistently underserved by mainstream financial institutions, with lack of credit identified as a paramount barrier to economic development of Indian Country (CDFI Fund, 2001; Jorgensen and Akee, 2017; Listokin et al., 2017).[1] As a result, in recent years, Native Community Development Financial Institutions (NCDFIs, in short) have emerged on or near American Indian reservations and tribal areas with the aim of improving Native communities' access to financial capital and services. Driven by a distinct social mission, NCDFIs epitomize a bottom-up, community-driven strategy to promoting financial self-determination, a critical precondition for economic prosperity within Native Nations (see, e.g., Cornell and Kalt, 2007).

Underwriting loans in Indian Country, however, presents some challenges. Among other obstacles, many borrowers in Native communities have had little or no exposure to credit markets, a consequence of the absence of banks and other financial intermediaries on or near reservations as well as general mistrust in mainstream financial institutions among Native populations (see, e.g., Jorgensen, 2016). Prospective NCDFI clients therefore often possess limited or poor credit histories (Dimitrova-Grajzl et al., 2015, 2022), a feature that aggravates lenders' asymmetric information problems and further contributes to financial exclusion of Native people and Native businesses.

For NCDFIs, conventional borrower risk measures such as credit scores, which are based on credit reports data, are therefore of limited use. Accordingly, in underwriting loans, NCDFIs resort to innovative, unconventional strategies that make use of NCDFIs' immersion in and knowledge of their communities. One such prominent practice has been to complement credit scores with alternative, soft-information-based metrics. Yet with the exception of one recent study that we identify below, the existing research has not systematically investigated the implications of the resulting approach to lending for NCDFI loan performance. The dearth of research on the topic is troublesome not only from the perspective of individual NCDFIs, who can only fulfill their social mission if they adopt lending practices that enhance their financial viability. It is also problematic from the standpoint of grantors and investors, who supply NCDFIs with financial capital, and government policymakers, who increasingly acknowledge NCDFIs as important vehicles of financial inclusion and socioeconomic progress in Native communities (see, e.g., GAO 2022, CRS 2022).

In the present paper we fill this gap in the literature by empirically examining whether NCDFI-used unconventional, soft-information-based measures of borrower risk are valuable in understanding delinquency of NCDFI-extended business loans. An evidence-based answer to this question provides insight into effectiveness of a common lending practice in the growing NCDFI

[1] 'Indian Country' refers to any ancestral or traditional Indigenous territories in the United States and the Indigenous people living within those territories, whether or not they live in a community that is distinctly Native in character.

industry. In addition, it enhances our understanding of the usefulness of soft information in addressing lending challenges beyond Indian Country.

To guide our investigation, we develop a simple conceptual framework and put forth a hypothesis grounded in the institutional specifics of the NCDFI industry and the scholarship on relationship lending. We then test our hypothesis utilizing a novel loan-level dataset on the universe of business loans extended by one leading NCDFI during the ten-year period between 2013 and 2022.

Our analysis thereby makes two central contributions to the literature. Firstly, we advance the scarce empirical literature on NCDFI lending and loan performance. Prior research, focused on NCDFI consumer lending, has shown that NCDFI-provided free financial counseling, another example of an unconventional lending practice, is associated with reduced prospects of NCDFI loans turning into unrecoverable debt (Dimitrova-Grajzl et al., 2023b). Recent evidence from eleven representative NCDFIs further indicates that soft-information-based measures of borrower risk such as client engagement may indeed be important in understanding NCDFI loan performance (Dimitrova-Grajzl et al., 2023a).

The present paper differs from and extends the analysis by Dimitrova-Grajzl et al. (2023a) in four key ways. We examine the complete set of loans issued by one major NCDFI between 2013 and 2022. Because our data contain information on the timing of key events in the life of each loan, we are able to employ survival analysis, an approach that allows us to incorporate pending (i.e., unresolved) loans and thereby mitigate sample selection concerns. Our dataset also features a consistent metric of delinquency, defined based on the timing of borrower's first missed loan payment.[2] And in studying drivers of business loan delinquency, we explore complementarities between hard- and soft-information-based measures of borrower risk. For all these reasons, our analysis provides the most comprehensive insight to date into the relevance of soft information for NCDFI lending.

At the same time, our paper adds to the voluminous literature on relationship lending (see, e.g., Kysucky and Norden, 2016; Elyasiani and Goldberg, 2004; Boot, 2000) and specifically on the use of soft information in gauging borrower risk and predicting loan performance (see, e.g., Chen et al., 2015; Cornée, 2019; Grunert et al., 2005; Neuberger and Räthke-Döppner, 2015; Wang, 2020; Ciampi et al., 2021). Our analysis extends this scholarship by elucidating the significance of soft information in the context of lending in the understudied NCDFI industry.

Institutional and Theoretical Background

NCDFIs in Context

In the U.S., Community Development Financial Institutions (CDFIs, in short) offer affordable financial products and development services specifically designed to meet the needs of consumers

[2] Not all NCDFIs use and report consistent delinquency measures. Due to data limitations and to facilitate comparisons across multiple NCDFIs, Dimitrova-Grajzl et al. (2023a) consider loans as delinquent if they were delinquent at any point during the loan process and by any amount.

and small businesses in communities underserved by traditional financial institutions (Kokodoko, 2015; Smith, 2008).[3] Most CDFIs are nonprofit loan funds, credit unions, and community development corporations, but the CDFI landscape also includes for-profit banks and either nonprofit or for-profit venture capital funds.

Native CDFIs (NCDFIs, henceforth), which constitute five percent of all certified CDFIs (CDFI Fund, 2022), concentrate their efforts on serving Native communities, thus directing at least half of their activities towards assisting American Indians, Alaska Natives, and/or Native Hawaiians. The majority of NCDFIs are managed by members of Native Nations and operate in tribal areas, with many NCDFIs further extending their services to individuals residing outside tribal lands (Jorgensen, 2016).

In following their social mission, NCDFIs exhibit several similarities with microfinance institutions (MFIs). Both sets of organizations aim to enhance credit accessibility, combat financial exclusion, and address economic disparities in targeted communities (see, e.g., Morduch, 1999; Cai et al., 2023; Mersland et al., 2019). Much like MFIs (see, e.g., Hudon and Sandberg, 2013; Morduch, 2000; Mersland and Øystein Strøm, 2014), NCDFIs also pursue their social goals while striving for financial sustainability.

However, NCDFIs distinguish themselves from typical MFIs in the specifics of their lending products and the unique characteristics of the socio-institutional environment that embeds them. For instance, while early MFIs in developing countries heavily relied on group lending, this approach was soon abandoned in Indian Country due to its incompatibility with the social structure and norms in Native communities (see, e.g., Pickering and Mushinski, 2001). Accordingly, the types of loan products and contractual schemes, including the use of collateral, employed by NCDFIs, often more closely resemble those utilized by traditional lenders than those used by MFIs operating in developing countries.

Furthermore, in Indian Country, financial exclusion may stem from factors beyond borrowers' insufficient or poor credit histories and lack of financial education, which often explain limited credit supply and demand in regions targeted by MFIs (Beck, 2015). In the U.S., there have been longstanding concerns about mainstream lenders discriminating against Native communities (CDFI Fund, 2001). Evidence indicates that, all else equal, consumers residing in predominantly American Indian areas receive lower bankcard credit limits compared to consumers living in areas with a small share of American Indian residents (Dimitrova-Grajzl et al., 2018). This suggests that mainstream lenders may be intentionally not funding creditworthy individuals and businesses in Native communities, a practice commonly known as redlining (see, e.g., Dymski, 1995). Via extending loans to those sidestepped by mainstream lenders, NCDFIs promote financial inclusion and credit market development in Indian Country.

[3] Elements of information presented in this and the ensuing subsection draw on Section 2 in Dimitrova-Grajzl et al. (2023a).

NCDFI Lending and Loan Performance: Hypothesis Development

In offering loans, NCDFIs face clients who have little to no credit history, rendering information asymmetries particularly significant concerns. To address this challenge, NCDFIs leverage their immersion in Native communities. Much like other small lenders serving clients with opaque credit histories (see, e.g., Berger and Udell, 2002; Berger et al., 2005; Uchida, 2011), NCDFIs gather insights about borrowers' behavior and traits which are rarely reflected in conventional, hard-information-based borrower risk metrics stressed by mainstream lenders. Consequently, NCDFIs rely heavily on relationship lending, an approach that is predicated on repeated lender-borrower interaction and entails the supplementing of hard-information-based measures of borrower risk such as credit scores with alternative ones based on soft information (see Berger and Udell, 2006).

Indeed, NCDFIs have a distinct advantage in effectively utilizing soft information. First, their comprehensive understanding of local social norms and culture plays a pivotal role in enabling relationship lending. Second, their relatively small size and horizontal organizational structure allow NCDFIs to delegate significant authority to loan officers. This is crucial for acquiring, interpreting, and leveraging soft information (see, e.g., Stein, 2002; Uchida et al., 2012).

Evidence from beyond Indian Country supports the notion that a lending approach combining hard with soft information can lead to improved outcomes for both lenders and borrowers. Specifically, the integration of hard and soft information gives rise to fewer defaults (see, e.g., Grunert et al., 2005; Chen et al., 2015; Cornée, 2019). This, in turn, enhances access to credit and fosters financial inclusion (see, e.g., Petersen and Rajan, 1994). In addition, relationship-based lending has been shown to play a role in easing borrowers' credit constraints during economic downturns (see, e.g., Ferri et al., 2019).

Nevertheless, relationship lending and utilization of soft information are not without their drawbacks. When there is limited competition among lenders, relying heavily on relationship lending can result in hold-up and soft-budget problems (see, e.g., Boot, 2000). These concerns may indeed arise in certain situations. However, we are not aware of any evidence indicating that NCDFIs encounter these issues. Moreover, the explicit focus of NCDFIs on ensuring that lending is beneficial to the borrower helps to address both of these potential problems. We thus hypothesize:

> H1: Unconventional soft-information-based measures of borrower risk, used by NCDFIs in underwriting loans, are valuable in elucidating NCDFI loan performance above and beyond conventional hard-information-based measures such as the credit score.

In what follows, we explore this hypothesis empirically using comprehensive loan-level data from one prominent NCDFI.

Data

Our data come from a NCDFI that serves individuals and businesses residing on or near the Cheyenne River Sioux Reservation in South Dakota.[4] Operating as a nonprofit loan fund, the NCDFI was established in 2000. Today, it is widely perceived to be one of the leaders in the NCDFI industry.

For research purposes, the NCDFI granted us access to the data on all 335 business loans that the organization issued between January 1, 2013 and December 31, 2022, our observation window. The data includes detailed information on the timing, status, and features of each loan as well as characteristics of borrowers, the overwhelming majority of whom are sole proprietors.

Events in the Life of a Loan

In line with its mission to foster financial inclusion, the NCDFI assists each loan applicant at securing the desired loan. With the NCDFI's staff guiding the client through the lending process, loan applications virtually never have to be denied.

For each loan, we know the closed deal date (the date of the start of the loan). Once a closed deal, a loan may experience delinquency, an event defined by borrower missing their scheduled loan payment for the first time. For every delinquent loan, we observe the date of delinquency. 53 loans (16 percent) in our sample experienced delinquency. Figure 1 shows the distribution of delinquent loans by timing of delinquency, measured with the number of days since closed deal. Most delinquencies arise early on, within the first two years or so since closed deal. But loans do become delinquent also much later, beyond 2000 days since closed deal.

Whether ever delinquent or not, a loan is resolved either by being paid in full or turning into bad debt. In the latter case, the loan is viewed unrecoverable by the NCDFI's lending committee and hence written off the books. For each loan that was resolved during our observation window, we also know the date when the loan was fully paid off or declared bad debt. From the 335 loans under consideration, 199 were paid in full. 27 were designated as bad debt. Especially important from the standpoint of our empirical approach that we elaborate on below, as many as 109 loans (33 percent) were still pending at the end of our observation window.

Table 1 shows the distribution of loans by delinquency status (delinquent or not) and final outcome (paid in full, bad debt, pending). Notably, the 53 delinquent loans in our sample either eventually turned into bad debt (27 loans) or were still pending at the end of our observation window (26 loans). No resolved loan that was at some point designated delinquent was paid in full. For resolved loans, therefore, delinquency perfectly predicts loan's status as bad (unrecoverable) debt. As we clarify in the section Methods, delinquency is, to use the terminology of survival analysis, the 'failure event' of our interest.

[4] The population of the Cheyenne River Sioux Tribe is about 12,000.

Measures of Borrower Risk

For each loan, we have information on three distinct borrower risk measures used by the NCDFI: character score, commitment to business, and credit score. The first two measures, the character score and commitment to business, are proprietary measures developed by the NCDFI to facilitate its own loan underwriting process. Both metrics rely heavily on soft information gathered by the NCDFI. The third measure, credit score, is a standard credit-bureau-generated measure of client creditworthiness based on hard information found in the credit reports data.[5]

At the NCDFI in question, loan underwriting is conducted in-house by the NCDFI's loan officers. The NCDFI endeavors to hire staff whose values align with the values of the organization. Through mentoring and collaboration, the NCDFI ensures that the loan officers have both the necessary level of comfort to deal with ambiguity as well as the skills to find appropriate solutions.

In assigning the commitment to business and character scores, the loan officers use a variety of available sources. Both scores are given at the time of the review of the client's file.

In determining the client's character as 'strong', 'medium', or 'weak', the loan officers focus primarily on the applicant's community business reputation, as well as on other publicly available history. In addition, the loan officer assesses if the client willingly disclosed all known accounts and key borrowing-related events. Further factors considered include client's planning for the future as evidenced by savings, qualifications to run the business (including past experience with running a business), and overall business and financial literacy.

In contrast, in evaluating client's commitment to business as 'strong', 'medium', or 'weak', the loan officer considers especially the client's actions that display their commitment to their business (e.g., the time, sweat equity, and any own assets they have put towards the business), their background knowledge about running a business, and their ability to tell the story (the arc) of the business from start to finish. Whenever feasible, the loan officer visits the client to learn more about how the client used available resources and pivoted during challenging times in the past.

Importantly, in assigning character and commitment to business scores, the loan officers do not use a predetermined formula but instead perform a holistic assessment. The organization's goal is not to provide a rigid scoring mechanism. Rather, the NCDFI aims to evaluate each client's strengths and identify areas for future improvement via relationship building and conversations.

In our data, all three NCDFI-utilized borrower risk measures were recorded prior to the closed deal date of each loan. All three measures can therefore be viewed as predetermined with respect to the loan events after the closed deal. For repeat clients, each of the three measures vary across loans.

[5] The precise approach to computing an individual's credit score can differ by model and credit bureau. However, all models and credit bureaus take into account factors such as individual's payment history, amount owed, length of credit history, new credit, and credit mix.

Table 2, top part, shows the descriptive statistics for our measures of borrower risk. 63 percent of loans are to borrowers whose character the NCDFI rated as strong. The NCDFI rated borrower character as medium in 29 percent of the loans, and as weak in three percent of the loans. Loans to borrowers with a strong, medium, and weak commitment to business respectively constitute 70 percent, 16 percent, and eight percent of all loans. We do not have information on borrower's character score and commitment to business for (the same) five percent of the loans.

For loans to borrowers who possess a credit score, mean credit score equals 647, which falls in the 'fair' range (credit score of at least 580 and less than 670). Loans to borrowers with a credit score designated as 'good or better' (credit score of 670 or more) constitute 33 percent of the sample. Borrowers with a 'poor' credit score (credit score less than 580) are recipients of 16 percent of the loans. Two percent of the loans were extended to borrowers with either no or very limited credit history; for those borrowers, the applicable credit bureau was unable to reliably estimate their prospects of loan default. Following the literature (see, e.g., Dimitrova-Grajzl et al., 2015), we refer to these borrowers as possessing a 'thin' credit file. About four percent of the loans are to clients who are not sole proprietors, but rather organizations. For loans to those borrowers, the credit score is not recorded because it cannot be linked to a specific individual. Credit score is genuinely missing (i.e., was not recorded by the NCDFI even though it exists) for eight percent of the loans.

To what extent do the distinct measures of borrower risk, used by the NCDFI, reflect different underlying variation and borrower risk factors? The data indicate that considerably so. At the loan level, pairwise correlations (not shown) among the indicators for character score 'not strong' (i.e., 'medium' or 'weak'), commitment to business 'not strong', and thin file or credit score poor are positive, but range between 0.14 and 0.36. Table 3 shows the distribution of loans by measures of borrower risk. Irrespective of whether the borrower has a thin file or poor credit score, each of the considered cells based on the borrower's character score and commitment to business features a non-zero number of loans. In sum, the three measures of borrower risk do reflect distinct variation in the data, allowing us to draw meaningful comparisons about the role of these measures in explaining loan performance. (In the section Results, we provide further, regression-based, evidence in support of this point.)

Other Loan and Borrower Characteristics

Table 2, bottom part, shows descriptive statistics for the remaining variables capturing loan and borrower characteristics. Mean loan amount, term, and interest rate are respectively $64,262, 61 months, and seven percent. 53 percent of the loans are second or further loans to the same client. The distribution of loans by year of closed deal is not uniform. Rather, the NCDFI issued an above-average number of loans early on during our observation window (28 percent in years 2013 and 2014) and then again after the onset of the Covid-19 pandemic (31 percent after January 31, 2020, when Covid-19 was declared a public health emergency). The NCDFI therefore actively aided the pandemic-related economic recovery in its community.

With regard to loan purpose, 46 percent of loans are microenterprise loans. The remaining loans are agricultural loans, general business loans or lines of credit, and loans to green enterprises. Concerning the NCDFI's source of lending capital, 65 percent of the loans were directly facilitated via a government-funded program (e.g., Native American CDFI Assistance Program, Revolving Loan Fund, Intermediary Relending Program, Rural Microentrepreneur Assistance Program, U.S. Treasury's CDFI Rapid Response Program). For the remaining loans, the typical source of lending capital were nonprofits, in particular Oweesta as the paramount NCDFI intermediary.

Nearly all extended loans are to sole proprietors. Women constitute 39 percent of the borrowers. The average borrower age at closed deal is 46 years. All but three percent of borrowers are from South Dakota and the overwhelming majority of borrowers (85 percent) are American Indian. 53 percent of the borrowers have received at least some post-secondary education. Average borrower household size is three members. Mean borrower household income is about $36,000. Congruent with the NCDFI's mission, for most loans (88 percent), borrowers were exposed to some form of NCDFI-provided financial counseling by the time of closed deal or during the loan's duration.

Methods

In assessing the role of soft-information-based measures of borrower risk for loan performance we focus on delinquency. By definition, every loan eventually declared bad debt was first delinquent: delinquency necessarily precedes the designation of a loan as unrecoverable debt. At the same time, during our observation window, no loan that experienced delinquency was paid in full (see the section Data). In our context, delinquency is thus a momentous event in the life of a loan and an early marker of poor loan performance.

To test our hypothesis H1, we first investigate whether the NCDFI-designed character and commitment to business scores, both soft-information-based metrics of borrower risk, help explain the prospects of business loan delinquency even after accounting for borrower's credit score. We then further examine if character score, commitment to business, and credit score interact in explaining the likelihood of business loan delinquency.

In our data, as many as 25 percent of loans that were never delinquent are still pending (see Table 1). The central methodological problem with pending loans is that they may differ systematically and in unobservable ways from the already-resolved loans in terms of delinquency risk. Dropping pending loans, as in standard regression analysis, would thus bias our results. To incorporate pending loans into the estimation, we use survival analysis, a methodological approach that directly mitigates sample selection concerns (see, e.g., Cleves et al., 2010). Moreover, in the life of a loan, only one of the events delinquency, declaration of bad debt, and payment in full can happen first. In estimating cause-specific hazards for delinquency, we thus follow the standard approach (see, e.g., Cleves et al., 2010: Ch. 17) and treat loans paid in full and non-delinquent pending loans as right-censored observations.[6]

Preliminaries

Figure 2 provides nonparametric evidence, in the form of Kaplan-Meier failure functions, on the role of different measures of borrower risk for business loan delinquency. Each part of the figure shows the probability that a loan becomes delinquent at a given number of days since the closed deal date while distinguishing between loans based on values of different measures of borrower risk.

The patterns in Figure 2 reveal important differences in the prospects of loan delinquency based on the borrower's credit score (part (c)) and, notably, character score (part (a)). In contrast, we do not see much evidence of importance of commitment to business in explaining business loan delinquency (part (b)). Figure 2, however, is purely descriptive: in illuminating the role of each particular borrower risk measure, we do not simultaneously control for the other borrower risk measures and for the remaining covariates. In what follows, to test hypothesis H1, we extend our analysis by simultaneously accounting for all three measures of borrower risk, controlling for a broad range of covariates and, in a subset of specifications, allowing for interacting effects among the three measures of borrower risk.

Main Empirical Approach

In our main analysis we rely on the Cox (1972) approach. In the Cox model, the covariates exert a multiplicative effect on the baseline hazard function, thereby facilitating ready interpretation of results. Moreover, unlike in parametric models, the key parameters are estimated without consideration of the full hazard function (see below). The semiparametric Cox model has thus been the most commonly utilized model in the applied survival analysis (Cleves et al., 2010: Ch. 9).

We let the hazard of delinquency for loan i take on the following form:

$$h_i(t|x_i, w_i) = h_{0i}(t) \exp(x_i'\beta + w_i'\gamma), \tag{1}$$

where t denotes time (in days) since the closed deal date. $h_{0i}(t)$ is the baseline hazard that is given no particular parameterization and need not even be estimated to ascertain the effects of covariates on delinquency hazard. Importantly, we let baseline hazard for loan i vary by whether the closed deal date precedes or comes after the start of the Covid-19 pandemic.[7] The pandemic was an unprecedented shock and, as such, it fundamentally shaped the risk of loan failure. Our decision to stratify loans by the timing of closed deal directly reflects these considerations. (In robustness

[6] Because every loan that turned into bad debt was first delinquent and with delinquency the failure event of our focus, loans eventually designated as bad debt are not right-censored.
[7] As the start of the pandemic we use January 31, 2020, the day when the Secretary of the Department of Health and Human Services declared the outbreak of 2019-nCoV a public health emergency.

checks, we show that none of our findings are sensitive to alternative approaches to incorporating the pandemic-specific risk.)

x_i is the vector of our focal explanatory variables, defined based on the three NCDFI-utilized measures of borrower risk (see Table 2). Depending on the specification, x_i can include interactions among the different measures of borrower risk. β is the vector of coefficients of primary interest.

w_i is the vector of our controls, with γ the corresponding coefficient vector. Concerning loan characteristics, we control for term (in months), interest (percent), amount (logged), instance (dummy for not first client loan), type (dummy for microenterprise), and capital source (dummy for government-funded). Regarding borrower characteristics, we control for gender (dummy for female), age at closed deal (in years), residence (dummy for not from South Dakota), race (dummy for not American Indian), attained education (dummy for at least some post-secondary), household size (dummy for member count exceeding three), household income (inverse hyperbolic sine, because sole proprietors can have negative income), and exposure to NCDFI-provided financial counseling (dummy for none).

Our data do not contain information about the exact nature of borrower's business such as industry classification or overall commercial success that could conceivably exert an independent effect on the hazard of loan delinquency. However, our inability to observe such information should not appreciably skew the results of our primary interest. The reason is that we would not expect our measures of borrower risk to vary systematically across specific industries, especially after controlling for a broad range of loan and borrower characteristics. At the same time, any influence of borrower's overall commercial success will be reflected in the already controlled-for contractual features of the loan (term and amount) as well as borrower's income.

Our focal explanatory variables (character score, commitment to business, credit score) and some of our controls (education, household size) have missing values (see Table 2). To maximize our sample size and statistical power, in our primary specifications we therefore also include (but do not report in the tables) dummies for the corresponding missing values. (Below, we clarify that none of our findings change if we instead drop those observations.)

The 335 business loans under investigation were extended to 159 distinct borrowers. To address the likely correlation of unobservables across loans of the same borrower, we base inference on heteroskedasticity-robust standard errors clustered at the borrower level, an approach resulting in 159 clusters.

Results

We report all estimates in the form of hazard ratios (exponentiated coefficients). A hazard ratio greater than one implies that the pertinent covariate is associated with an increase in delinquency hazard. In contrast, a hazard ratio smaller than one indicates that the applicable covariate is associated with a decrease in delinquency hazard.

Baseline Results

Table 4 present our results for specifications where we examine the role of each of the three borrower risk measures separately, without allowing for their interactions. Columns (1)-(3) show the estimates when we capture the three different measures of borrower risk with three basic indicators: for weak or medium (i.e., not strong) character score and commitment to business, and for thin file or poor credit score. Columns (4)-(6) show the estimates where we instead use indicators for finer measures of borrower risk, distinguishing between medium and weak character score and commitment to business, and among thin file, poor credit score, and fair credit score. In all specifications, the omitted categories are loans for which the borrower possesses strong character score and strong commitment to business. For credit score, the omitted category is fair or better for specifications in columns (1)-(3), and good or better for specifications in columns (4)-(6). We interpret the results based on the specifications featuring the full set of loan and borrower controls (columns (3) and (6)).

The results imply four key substantive findings. First, congruent with hypothesis H1, delinquency hazard is statistically significantly negatively related to character score. Based on the specification in column (3), borrower possessing weak or medium (i.e., not strong) character score is associated with a 120 percent increase in delinquency hazard, all else equal. The estimates in columns (4)-(6) further indicate that this association is driven primarily by borrower possessing weak character score: we do not see a statistically significant impact on delinquency hazard when borrower has medium as opposed to strong character score (column (6)).

Second, irrespective of the specification, we do not find any evidence of a relationship between delinquency hazard and borrower's commitment to business. The estimated hazard ratios for the indicators of the strength of commitment to business are never statistically significantly different from one (the non-exponentiated coefficients are not statistically significantly different from zero). When it comes to the NCDFI's commitment to business metric, we thus do not find evidence in favor of hypothesis H1.

Notably, the lack of a statistically significant effect of commitment to business cannot be explained by collinearity between the indicators for different levels of commitment to business and the indicators based on other measures of borrower risk. We continue to see no evidence of a relationship between delinquency hazard and commitment to business even when we altogether exclude from the model the indicators for character score and credit score (results not shown). We also explicitly tested for multicollinearity to formally gauge the extent to which our borrower risk measures reflect distinct underlying variation in the data. For the Cox model, there exists no standard approach to assessing multicollinearity. Using the set of explanatory variables as featured in columns (3) and (6) of Table 4, we thus estimated OLS regressions where our outcome variable was an indicator for whether a loan had been delinquent. The mean and the maximum variance inflation factors (VIFs) were 1.51 and 2.82 for the specification as in column (3) of Table 4, and 1.52 and 2.86 for the specification as in column (6) of Table 4. These VIF values are notably below the threshold value of 10 indicative of multicollinearity problems (Wooldridge 2013: 98). In sum, our results are not an artifact of multicollinearity.

Third, delinquency hazard is positively associated with borrower possessing credit score rated less than good. In particular, borrower having poor as opposed to good or better credit score is associated with a 183 percent increase in delinquency hazard (column (6)). Borrower possessing fair as opposed to good or better credit score is associated with a 141 percent increase in delinquency hazard (column (6)).

Fourth, borrower having a thin file, as opposed to credit score that is good or better, is never statistically significantly related to loan delinquency hazard (columns (4)-(6)). Given the comparatively rich set of borrower characteristics that we are able to control for and the fact that the NCDFI in question, by virtue of its mission, seeks to extend credit whenever possible, this result cannot be explained by the kinds of sample-selection concerns that can arise in non-NCDFI settings, where borrowers with thin files may differ systematically from other borrowers with respect to unobservable traits relevant to converting a loan application into an approved loan. We therefore do not find evidence in support of the argument, often emphasized by mainstream lenders, that extending credit to borrowers with very limited prior credit history is distinctly risky, all else equal. Rather, based on our analysis, the fostering of financial inclusion via provision of credit to borrowers with limited credit histories is not only consistent with the NCDFIs' mission, but also justifiable on risk grounds.

Exploring Complementarities

We next investigate complementarities in the use of the three NCDFI-used measures of borrower risk in explaining delinquency hazard. To this end, we include in the vector of focal explanatory variables on the right-hand-side of expression (1) seven pertinent indicators, each depicting a different scenario with regard to borrower's character score (strong, not strong), commitment to business (strong, not strong), and credit score (thin file or poor credit score, fair or better credit score). Table 3 summarizes the pertinent scenarios, providing information on the loan counts under each scenario.

Table 5 shows the estimates based on the resulting specifications. The omitted (benchmark) category is loans for which both borrower's character score and commitment to business are strong and borrower's credit score is fair or better. In interpreting our findings, we again focus on the specification with the full set of controls (column (3)).

Resonating with hypothesis H1, the estimates in Table 5 indicate important complementarities among different measures of borrower risk. Our results therefore provide strong evidence in support of an NCDFI loan underwriting approach that relies on the combined use of hard and soft information in assessing borrower risk.

First and foremost, our analysis shows that the implied change in delinquency hazard is the greatest when borrower is rated poorly on all three NCDFI-utilized risk measures, that is, when borrower has a thin file or poor credit score together with weak or medium character score and commitment to business. In this scenario, the delinquency hazard is 268 percent larger than in the benchmark scenario, all else equal.

Importantly, it is the confluence of multiple precarious borrower circumstances that underpins the above-noted statistically significant association. We do not find evidence that, when borrower already has weak or medium character score, additionally possessing a thin file or poor credit score and weak or medium commitment to business is related to an increase in delinquency hazard above and beyond that implied by possessing weak or medium character score alone (p=0.781). Similarly, when borrower already has weak or medium character score and a thin file or poor credit score, additionally possessing weak or medium commitment to business is not associated with a statistically significant rise in delinquency hazard above and beyond that stemming from weak or medium character score and a thin file or poor credit score (p=0.912).

Second, possessing strong commitment to business, but weak or medium character score and thin file or poor credit score, is associated with a 249 percent increase in delinquency hazard relative to the benchmark scenario. Once more, it is the simultaneous combination of weak or medium character score and thin file or poor credit score that underpins this relationship. When borrower with strong commitment to business already has weak or medium character score, additionally possessing thin file or poor credit score is not associated with a statistically significant rise in delinquency hazard above and beyond that related to having weak or medium character score (p=0.833). Analogously, when borrower with strong commitment to business already has a thin file or poor credit score along, additionally possessing weak or medium character score is not related to an increase in delinquency hazard above and beyond that associated with a thin file or poor credit score (p=0.282).

Sensitivity Analysis

We performed three key sets of robustness checks. For brevity, we only summarize our findings.[8] First, we re-estimated our models upon dropping observations with missing values for the three measures of borrower risk. Second, we estimated Cox models where, instead of allowing baseline hazard to vary with the timing of closed deal relative to the pandemic, the pandemic period was assumed to exert a multiplicative effect on delinquency hazard. None of our findings reported in the previous two sections change as a result.

Third, we estimated fully parametric models. The Weibull model fit our data best. All but two of our key findings were unaffected by relying on a parametric instead of a semiparametric (Cox) approach. Under the Weibull model, however, possessing a thin file was associated with a higher delinquency hazard and the largest increase in delinquency hazard relative to the benchmark scenario arose when borrower simultaneously possesses a thin file or poor credit score and weak or medium character score, but strong commitment to business. While fully parametric models can generate efficiency gains, they are also inherently more prone to misspecification bias than the semiparametric Cox model. We thus do not view the Weibull estimates as supplanting or

[8] Full results are available upon request.

dismissing the pertinent results reported in the previous subsections. But we do suggest that the subset of our findings for which the semiparametric and fully parametric approaches disagree is interpreted with some caution.

Discussion

The unique data utilized in the present paper have allowed us to track all critical events in the life of an NCDFI business loan and employ survival-analysis techniques that are better suited for addressing sample selection issues than conventional regression-based methods. In comparison with earlier work that sheds light on the use of soft information in NCDFI lending (Dimitrova-Grajzl et al. 2023a), our present analysis thereby illuminates more clearly which NCDFI-created, soft-information-based measures of borrower risk are especially valuable for understanding NCDFI loan delinquency, and thus what aspects of loan underwriting enhance financial viability of NCDFIs and foster financial inclusion in Native communities. More generally, our inquiry offers new quantitative insight into the operations of the expanding but understudied NCDFI industry.

Implications for Practice and Policy

Our analysis offers several important implications for NCDFI lending practices and public policy toward NCDFIs. Our evidence indicates that, in assessing a client's character score, the NCDFI under scrutiny makes productive use of its immersion in and knowledge of the local community to cope with scant credit histories of many Indian Country borrowers and associated lending risks. Our research thereby highlights an example of a soft-information-based risk-management practice that other NCDFIs could emulate in their effort to increase the prospects of their own financial sustainability and enhance credit market participation in their communities.

At the same time, our investigation underscores the benefits of a lending practice that, while not typically adopted by large-scale mainstream lenders, should be valued by external grantors, investors, and government policymakers when considering NCDFIs as vehicles of economic progress in Native communities. Prior research on consumer lending shows that NCDFI-provided free financial counseling of clients can be effective at mitigating lending risks (Dimitrova-Grajzl et al., 2023b). Our results in this paper imply that NCDFIs also possess the capacity to run a compelling in-house loan underwriting process. Applied to the context of the NCDFI industry as a whole, our empirical findings do not provide grounds for replacing the current decentralized approach to loan underwriting, whereby each NCDFI underwrites its own loans, with a single loan underwriting scheme centralized at the NCDFI industry-level, an alternative approach considered by some practitioners.

But our investigation also reveals that the use of soft information in NCDFI lending is not a panacea. In our data, the commitment to business score, the other NCDFI-generated soft-information-based metric, shows no detectable relationship with the hazard of business loan delinquency. For practical purposes, our findings thus indicate that the commitment to business metric should either be phased out or fine-tuned by the NCDFI under scrutiny to reflect more relevant dimensions of borrower risk.

Importantly, our findings should not be interpreted as advocating NCDFIs' exclusive reliance on soft-information-based measures to manage borrower-related lending risks. As our analysis demonstrates, the conventional credit-bureau-generated, hard-information-based credit score (if a borrower has one) is both a salient loan delinquency predictor on its own and a factor that exhibits important complementarities with NCDFI-generated, soft-information-based measures. Moreover, in the context of relationship lending, a lender's overemphasis on soft information could devolve into borrower exploitation (see, e.g., Boot 2000). Such lending strategies are of course inherently incompatible with NCDFIs' mission, but caution should nevertheless be exercised when formulating industry-wide best practices on the use of soft information for assessing borrower risk.

Limitations and Further Research

Our study is not without limitations. First, our findings are based on business loan data of one NCDFI. But NCDFIs differ in their lending practices, organization, specific products, characteristics of the client base, and even details of social mission. Future work should explore to what extent our findings about the relevance of soft information in NCDFI loan underwriting extend to other NCDFIs.

Second, in examining business loan delinquency, we have focused on the role of two soft-information-based measures of borrower risk designed by the NCDFI under consideration. Yet the performance of business loans arguably also depends of many other factors that we have not explored in our analysis. Some of them, such as the specifics of borrower's business, were unobservable to us in the present analysis. Follow-up research should explore the importance of these and related factors for delinquency of NCDFI business loans.

Finally, it would be interesting to examine whether soft-information-based measures of borrower risk are perhaps valuable in explaining outcomes other than loan performance. Community-wide outcomes that resonate with NCDFIs' social mission, such as new jobs created, may be particularly relevant in this regard.

Conclusion

In Indian Country, where many borrowers have scant credit histories, indiscriminate reliance on hard-information-based measures of borrower risk, such as credit-bureau-produced credit scores, merely exacerbates financial exclusion. In providing credit, Native Community Development Financial Institutions (NCDFIs) therefore often rely on their own, soft-information-based, measures. Drawing on fine-grained business loan data of one major NCDFI, a nonprofit loan fund, we have demonstrated that aspects of NCDFI-acquired soft information about borrowers can be highly valuable in anticipating loan performance. Our evidence thus lends support to NCDFIs' unique mission-driven loan underwriting process and, more broadly, approach to fostering financial inclusion. Given the central importance of NCDFIs for enhancing prosperity of

Native communities, NCDFI lending practices and performance constitute an important and highly policy-relevant area of inquiry awaiting further investigation.

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Table 1: The distribution of loans by delinquency status and final outcome

	Delinquent	Never delinquent	Total
Paid in full	0	199	199
Bad debt	27	0	27
Pending	26	83	109
Total	53	282	335

Notes: The table reports the distribution of loans by whether loan was ever delinquent and the observed loan outcome (paid in full, bad debt, pending).

Table 2: Descriptive statistics for key variables

Variable	Mean	S.D.	Min.	Max.	Obs.
Measures of borrower risk					
Character score strong (dummy)	0.633	0.483	0	1	335
Character score not strong (dummy)	0.313	0.465	0	1	335
Character score medium (dummy)	0.287	0.453	0	1	335
Character score weak (dummy)	0.027	0.162	0	1	335
Character score missing (dummy)	0.054	0.226	0	1	335
Commitment to business strong (dummy)	0.704	0.457	0	1	335
Commitment to business not strong (dummy)	0.242	0.429	0	1	335
Commitment to business medium (dummy)	0.164	0.371	0	1	335
Commitment to business weak (dummy)	0.078	0.268	0	1	335
Commitment to business missing (dummy)	0.054	0.226	0	1	335
Credit score	646.7	68.1	485	805	291
Credit score good or better (dummy)	0.328	0.470	0	1	335
Credit score fair (dummy)	0.379	0.486	0	1	335
Credit score poor (dummy)	0.161	0.368	0	1	335
Thin file (dummy)	0.021	0.143	0	1	335
Credit score missing (dummy)	0.075	0.263	0	1	335
Credit score not applicable (dummy)	0.036	0.186	0	1	335
Loan characteristics					
Term (in months)	60.7	52.8	2	360	335
Interest rate (in percent)	7.2	1.7	0	12	335
Amount (in $)	64,262.1	122,796.0	454.5	1,414,000.0	335
Not first loan (dummy)	0.525	0.500	0	1	335
Closed deal in pandemic (dummy)	0.313	0.465	0	1	335
Microenterprise loan (dummy)	0.460	0.499	0	1	335
Government funded (dummy)	0.648	0.478	0	1	335
Other borrower characteristics					
Female (dummy)	0.385	0.487	0	1	335
Age at closed deal (in years)	46.4	13.7	21	91	335
Not from South Dakota (dummy)	0.030	0.170	0	1	335
Not American Indian (dummy)	0.155	0.363	0	1	335
Education post-secondary (dummy)	0.525	0.500	0	1	335
Education missing (dummy)	0.072	0.258	0	1	335
Household size (members count)	3.1	2.6	1	36	315
Household size > 3 (dummy)	0.394	0.489	0	1	335
Household size missing (dummy)	0.060	0.237	0	1	335
Household income (in $)	35,954.3	40,251.8	-147,263.0	150,000.0	335
No financial counseling (dummy)	0.125	0.332	0	1	335

Notes: The table reports the descriptive statistics for key variables. The unit of observation is a loan. For commitment to business and character score, 'not strong' refers to 'medium' or 'weak'. Credit score missing=1 depicts the scenario when the credit score should have been recorded but was not (genuinely missing data). This scenario is distinct from the scenario when Thin file=1. In the latter case, the credit score is not reported because of the client's nonexistent or limited credit history that prevents the credit bureau from computing a credit score. Credit score not applicable=1 depicts the scenario where the borrower is an organization as opposed to a sole proprietor and thus a credit score could not be linked to a borrower. Household income can be negative when the sole proprietor incurs losses.

Table 3: The distribution of loans by measures of borrower risk

Part A: Thin file or credit score poor			
	Commitment to business strong	Commitment to business not strong	Total
Character score strong	14	6	20
Character score not strong	23	18	41
Total	37	24	61
Part B: Credit score fair or better			
	Commitment to business strong	Commitment to business not strong	Total
Character score strong	140	38	178
Character score not strong	43	15	58
Total	183	53	236

Notes: The table shows the distribution of loans by the three utilized measures of borrower risk. Part A shows the distribution for different values of commitment to business and character score when the borrower has either a thin file or a poor credit score. Part B shows the analogous distribution when the borrower's credit score is fair or better. The total number of considered loans is 297. The excluded loans are those featuring a missing value for any of the measures of borrower risk.

Table 4: Measures of borrower risk and delinquency hazard

	(1)	(2)	(3)	(4)	(5)	(6)
Character score not strong	1.617	2.417**	2.204**			
	(0.596)	(0.855)	(0.857)			
Character score weak				4.388**	9.592***	9.726**
				(3.220)	(7.597)	(9.702)
Character score medium				1.275	1.932*	1.580
				(0.487)	(0.744)	(0.630)
Commitment to business not strong	0.813	0.845	0.812			
	(0.314)	(0.328)	(0.278)			
Commitment to business weak				0.382	0.470	0.527
				(0.243)	(0.316)	(0.439)
Commitment to business medium				0.899	0.904	0.894
				(0.363)	(0.362)	(0.313)
Thin file or credit score poor	1.576	1.681	1.653			
	(0.604)	(0.605)	(0.660)			
Thin file				1.326	1.759	0.991
				(1.567)	(1.883)	(0.854)
Credit score poor				2.852*	2.880*	2.832*
				(1.665)	(1.652)	(1.711)
Credit score fair				2.316*	2.260*	2.141*
				(0.994)	(0.995)	(0.923)
Loan characteristics	No	Yes	Yes	No	Yes	Yes
Borrower characteristics	No	No	Yes	No	No	Yes
Failures (delinquent loans)	53	53	53	53	53	53
Observations (all loans)	335	335	335	335	335	335
Log pseudolikelihood	-227.3	-218.2	-211.4	-222.2	-213.1	-206.0

Notes: The table shows the estimated hazard ratios (exponentiated coefficients) based on the Cox model stratified by whether the loan was closed pre or during the pandemic period. The failure event is loan becoming delinquent (borrower misses a scheduled payment for the first time). The omitted category is strong for character score and commitment to business, fair or better for credit score for specifications in columns (1)-(3) and good or better for credit score for specifications in columns (4)-(6). See the subsection Main Empirical Approach for the included loan and borrower characteristics. All estimated models include (but do not report) dummies for missing commitment to business, character score, and credit score, as well a dummy for credit score not applicable (see Table 2). Models in columns (3) and (6) further include dummies for missing borrower household size and education. Heteroskedasticity-robust standard errors clustered at the borrower level in parentheses. ***, **, and * indicate *p*-value smaller than 0.01, 0.05, and 0.1, respectively.

Table 5: Interactions among measures of borrower risk and delinquency hazard

	(1)	(2)	(3)
Thin file or credit score poor, character score not strong, commitment to business not strong	2.179	3.739*	3.676*
	(1.390)	(2.687)	(2.618)
Credit score fair or better, character score not strong, commitment to business not strong	1.131	1.387	1.181
	(0.869)	(0.992)	(0.868)
Thin file or credit score poor, character score strong, commitment to business not strong	5.261**	6.240***	4.930
	(4.327)	(4.207)	(5.081)
Thin file or credit score poor, character score not strong, commitment to business strong	2.507	4.424**	3.492*
	(1.644)	(3.081)	(2.301)
Credit score fair or better, character score strong, commitment to business not strong	1.001	1.116	1.066
	(0.516)	(0.632)	(0.538)
Credit score fair or better, character score not strong, commitment to business strong	2.674**	3.717***	3.100**
	(1.061)	(1.586)	(1.418)
Thin file or credit score poor, character score strong, commitment to business strong	1.773	1.577	1.428
	(1.115)	(0.904)	(0.979)
Loan characteristics	No	Yes	Yes
Borrower characteristics	No	No	Yes
Failures (delinquent loans)	53	53	53
Observations (all loans)	335	335	335
Log pseudolikelihood	-224.9	-215.6	-209.4

Notes: The table shows the estimated hazard ratios (exponentiated coefficients) based on the Cox model stratified by whether the loan was closed pre or during the pandemic. The failure event is loan becoming delinquent (borrower misses a scheduled payment for the first time). The omitted category is loans where the borrower's character score and commitment to business are strong and the borrower's credit score is fair or better. See the subsection Main Empirical Approach for the included loan and borrower characteristics. The estimated models include (but do not report) dummies for missing character score, commitment to business, and credit score, as well a dummy for credit score not applicable (see Table 2). Model in column (3) further includes dummies for missing borrower household size and education. Heteroskedasticity-robust standard errors clustered at the borrower level in parentheses. ***, **, and * indicate *p*-value smaller than 0.01, 0.05, and 0.1, respectively.

Figure 1: The distribution of delinquent loans by timing of delinquency

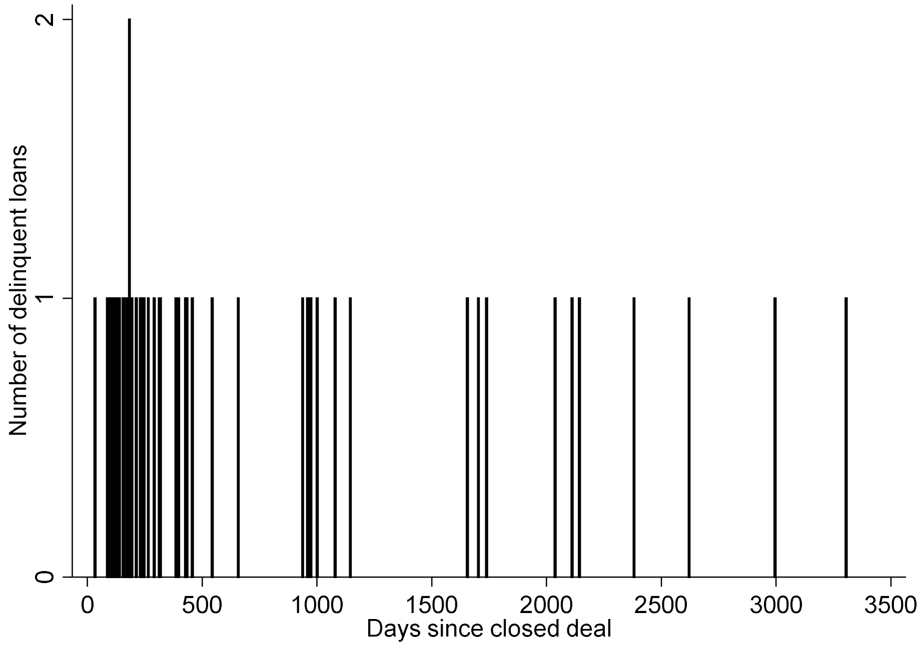

Figure 2: Probability of delinquency and measures of borrower risk