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Abstract

Native Community Development Financial Institutions (NCDFIs) fill credit-supply gaps and promote financial inclusion in Native communities. To mitigate lending risks and aid clients, NCDFIs often rely on unconventional lending practices, such as providing clients with free financial counseling. Drawing on uniquely detailed loan-level data from one prominent NCDFI and using survival analysis, we find that borrower exposure to NCDFI-provided financial counseling appreciably reduces the prospects of loan failure when the borrower has had limited prior credit-market experience. Our findings are indicative of the importance of the growing, but understudied, NCDFI industry for financial development of Indian Country.

Keywords: Native CDFIs, financial counseling, credit history, loan performance, financial inclusion, Indian Country

JEL Classifications: G21, G53, G11, J15, O16, P43

1. Introduction

Indian Country has been historically underserved by mainstream financial institutions (Jorgensen, 2016; Listokin et al., 2017; Dimitrova-Grajzl et al., 2015, 2018).[1] In recent years, this credit-supply gap has been partly filled by the emergence of Native Community Development Financial Institutions (NCDFIs): loan funds, credit unions, and other financial organizations dedicated to serving Native communities by providing affordable loan products and culturally tailored financial services. NCDFIs embody a private-sector, market-based approach to enhancing financial inclusion and self-determination, thereby promoting economic prosperity within Native nations (Cornell and Kalt, 2007; Cornell and Jorgensen, 2022).

Extending credit in Indian Country, however, poses several challenges. A significant share of NCDFI clients have limited or no credit history, possess scant financial knowledge, and face income insecurity. Thus, loans can turn into unrecoverable debt. To mitigate credit risks and to aid clients, NCDFIs develop innovative lending strategies.

In this paper, we empirically investigate the consequences for NCDFI loan performance of one such lending practice: free financial counseling of clients. Drawing on loan-level data from a leading NCDFI, we explore whether and when the NCDFI-extended 'helping hand' improves the prospects of successful loan repayment—an outcome that benefits the NCDFI, the borrower, and the Native community striving to achieve financial inclusion.

Our analysis thereby offers unique, evidence-based insight into the functioning of financial organizations that play an increasingly important role in facilitating socioeconomic development in Indian Country (Kokodoko, 2015, 2017; Jorgensen and Taylor, 2015; Dewees and Sarkozy-Banoczy, 2008; Dimitrova-Grajzl et al., 2022). No prior study has examined the consequences of NCDFI client counseling for NCDFI loan performance, even though client-centered approaches lie at the heart of NCDFIs' mission.

More broadly, our research contributes to the empirical literature on the importance of financial education for economic and credit outcomes (Hastings et al., 2013; Lusardi and Mitchell, 2014). Our results suggest that activities undertaken by lenders themselves to aid and support, as opposed to supervise, clients may be an important determinant of loan outcomes—a possibility largely overlooked by existing empirical studies on loan repayment (Albanesi and Vamossy, 2019; Barbaglia et al., 2021; Butaru et al., 2016).

2. Institutional Background

Our data come from an NCDFI that serves consumers residing on or near a major American Indian reservation in South Dakota. The NCDFI in question has been in operation since 2000 and is widely perceived to be one of the leading nonprofit organizations promoting Native community and economic development.

Like other NCDFIs, our NCDFI offers its borrowers the opportunity to participate in financial counseling (counseling, in short). All counseling is free of charge and provided by the NCDFI staff. The NCDFI implements counseling via training (group) and coaching (individual) sessions. Training occurs in a class-like format and focuses on financial literacy skills. Coaching takes place

[1] *Indian Country* is defined as 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.

via one-on-one meetings. Expanding on lessons from the training session, the coach counsels the client about budgeting, credit scores, taxes, and establishing future goals. Counseling starts shortly before and continues a few months after the start of the loan (that is, after the closed deal). Borrower participation is voluntary, but often recommended by the NCDFI and frequently requested by borrowers themselves.

3. Data

We have data on all 441 consumer loans that the NCDFI issued as first loans to the corresponding 441 borrowers from 2008 up to the official announcement of the COVID-19 pandemic on March 11, 2020. We focus on the set of first loans issued to each client to allow for the cleanest study of the interacting role of NCDFI-provided counseling and borrower credit history on loan delinquency, devoid of confounding effects from repeated lender-client interaction and endogenous changes in credit history.

Table 1 shows the descriptive statistics for all loans and subsamples of loans based on whether the client possesses a credit score. Most loans in our data are credit-builder loans offered to clients with limited or no credit history for purposes of building a positive credit history. The mean loan amount is small: less than $2,500. Of the borrowers represented in our data, 27 percent do not possess a credit score—they have a 'thin' credit file—at the time of the closed deal. For borrowers who have a credit score, the mean score (594) is at the lower end of the 'fair' credit score range.

Table 2 gives the distribution of loans by borrower exposure to counseling (in hours) for all loans, loans to borrowers without a credit score, and loans to borrowers with a credit score. Of all borrowers, 28 percent received some counseling. Among loans to borrowers without a credit score, 17 percent of borrowers received counseling. Among loans to borrowers with a credit score, 32 percent of borrowers received counseling. Conditional on receiving at least some counseling, the median exposure to counseling across all three categories (borrowers with a credit score, without a credit score, and combined) is 0.5 hours.

For each loan, we know the closed deal date (the start of the loan). For any loan that was resolved—paid in full or turned into bad debt (i.e., deemed unrecoverable by the NCDFI and thus written off the books)—during our observation window, we know the date when the loan was fully paid off or declared bad debt. Of the 441 loans in our data, 321 were paid in full and 60 turned into bad debt. The remaining 60 loans were still pending at the end of our observation window, so are *right-censored*, the statistical term used to describe situations where a study ends before the event has occurred.

Figure 1 shows the non-parametrically estimated probability that a loan turns into bad debt at any given number of days since the closed deal date, distinguishing between loans where the borrower has received counseling and loans where the borrower has not received counseling. The data suggest important interaction effects between counseling and borrowers' prior credit-market experience: only for loans to borrowers with a thin credit file is the likelihood of a loan turning into bad debt consistently lower when the borrower has received counseling (Figure 1, panel a). For loans to borrowers with a credit score (Figure 1, panel b) and for all loans (Figure 1, panel c), there is no clear difference in the prospects of loan turning into bad debt between the loans involving borrower counseling and the loans not involving borrower counseling.

Figure 1, however, paints a purely descriptive picture of the role of borrower's exposure to counseling and its interaction with borrowers' prior credit-market experience for loan performance. In the ensuing analysis, we address the issue of causality more explicitly.

4. Empirical Approach

To ascertain whether and how counseling affects the prospects of a loan turning into bad debt, we must confront two key empirical challenges: the nonrandom assignment of counseling and the right-censored nature of our data. We address the first challenge using an identification approach based on selection on observables and a careful conceptual argument. We tackle the second challenge by employing methods of survival analysis.

4.1. Identification

The decision of the NCDFI to offer counseling and of the client to participate in counseling depends on a variety of factors, including borrower and loan characteristics. Examples include the borrower's education and loan type, which we observe and control for. Whether a borrower receives counseling, however, also depends on a variety of their personal and professional circumstances that likely exert an independent effect on loan performance but remain unobservable to us. Such unobservables would bias our analysis even upon controlling for the full set of observed loan and borrower characteristics.

Nevertheless, in our context, an identification strategy based on selection on observables provides informative estimates of the effect of financial counseling on loan performance. All else equal, the NCDFI will tend to engage its client in counseling when the inherent prospects of loan default are deemed comparatively greatest. Based on pairwise correlations (not shown), in our data a borrower is indeed more likely to receive counseling when, for example, the extended loan is a credit-builder loan, the loan amount is large, and the borrower's household income is low. Thus, if after controlling for the full set of observable loan- and borrower-level covariates we find that the likelihood of a loan turning into bad debt is lower when the borrower undergoes counseling, the corresponding estimate underestimates the absolute magnitude of the true counseling effect. Our analysis is therefore best viewed as identifying the lower bound on the actual (absolute) size of the impact of counseling on the prospects of a loan turning into bad debt.

4.2. Survival Analysis

Nearly 14 percent of the loans in our data are still pending. Pending loans may differ systematically in terms of risk from the already resolved loans; dropping pending loans would thus bias the analysis. To incorporate pending loans into the estimation, we use survival analysis. A loan can be resolved either via being paid in full or turning into bad debt. For each loan, only one of the two modes of resolution can occur first: payment in full and declaration of bad debt are competing risk events. To estimate cause-specific effects for the incidence of bad debt, we therefore treat loans paid in full and pending loans as right-censored observations. This approach yields valid estimates of cause-specific effects without assuming independence of competing risks (Cleves et al., 2010).

We use the (semiparametric) Cox model. We let the hazard of bad debt for loan i take on the following form:

$$h(t|x_i, w_i) = h_0(t)\exp(x_i'\beta + w_i'\gamma), \tag{1}$$

where t denotes time (in days) since the closed deal date and $h_0(t)$ is the baseline hazard. x_i is the vector of our focal explanatory variables: given Figure 1, we incorporate interactions between borrowers' exposure to NCDFI-provided counseling and possession of a credit score. w_i is the vector of the remaining borrower and loan characteristics, or controls. We base inference on heteroscedasticity-robust standard errors.

5. Results and Discussion

We report all results in the form of hazard ratios (exponentiated coefficients). A hazard ratio greater than 1 implies that the variable in question is associated with an increase in the hazard of bed debt, and a hazard ratio smaller than 1 implies a decrease in the hazard of bad debt.

5.1. Main Results

Table 3 presents our main results. Columns 1–3 show the estimates when we explore the impact of counseling along the extensive margin, thus modeling the interaction of borrower exposure to any amount of counseling and borrower possession of a credit score. Columns 4–6 show the estimates when we instead focus on the intensity of counseling and its interacting effect with borrower possession of a credit score. We distinguish between whether the borrower received less than half an hour versus at least half an hour of counseling. In all specifications, the omitted category consists of loans for which the borrower neither received counseling nor possesses a credit score. We interpret the results based on the specifications featuring the full set of loan and borrower controls (columns 3 and 6).

Our analysis reveals four core findings. First and foremost, counseling is associated with a reduction in the hazard of bad debt, but only when the borrower has a thin credit file. When the borrower does not have a credit score, counseling is associated with an 82.1-percent decrease in hazard of bad debt (column 3). In contrast, when the borrower has a credit score, counseling is not statistically significantly related to the hazard of bad debt: the *p*-value for test of equality of effects of no counseling versus some exposure to counseling, conditional on borrower having a credit score, equals 0.657.

Second, the intensity of borrower exposure to counseling matters. When the borrower has a thin credit file, counseling is associated with a reduction in hazard of bad debt only when the borrower has received at least half an hour of counseling. In that case, counseling is associated with an 87.8-percent reduction in hazard of bad debt (column 6). In contrast, exposure to less than half an hour of counseling is not statistically significantly related to the hazard of bad debt irrespective of whether the borrower has a credit score (*p*-values for the tests of equality of applicable effects equal 0.248 and 0.265).

Third, the implied effectiveness of counseling at reducing the hazard of bad debt when the borrower has a thin credit file is as large as the effect of possessing a credit score: *p*-values for tests of equality of corresponding effects based on the estimates in columns 3 and 6 equal 0.657 and 0.862, respectively. Thus, our analysis suggests that, from the perspective of loan performance, NCDFI-provided counseling serves as a substitute for borrowers' prior credit-market experience.

Fourth, concurrently receiving counseling and possessing a credit score does not reduce the hazard of bad debt beyond the effect of only possessing a credit score or only receiving counseling: *p*-values for tests of equality of corresponding effects equal 0.965 and 0.442 based on the estimates in column 3, and 0.779 and 0.832 based on the estimates in column 6 when considering at least half an hour of counseling. We therefore do not find evidence of noteworthy complementarities between NCDFI client counseling and borrowers' prior credit-market experience in reducing the prospects of loan failure.

5.2. Robustness

We explored several alternative model specifications. We estimated a stratified Cox model, allowing the baseline hazard of bad debt to differ by loan type (credit-builder, hardship, holiday, and other loans). We ran a series of parametric hazard models. The Weibull model fit our data best. The estimated hazard ratios obtained upon estimating stratified Cox and Weibull models are displayed in Table 4. The results are fully congruent with our main results featured in Table 3. Finally, we examined the counseling effect separately for loans for which the borrower has a thin file and loans where the borrower possesses a credit score. Our findings (not shown) were once more fully consistent with those reported above.

6. Concluding Reflections

Our analysis shows that, when the borrower has a thin credit file, sufficient borrower exposure to NCDFI-provided, free financial counseling is associated with a considerable reduction in the prospects of a loan turning into bad debt. Given our identification approach (selection on observables) and the fact that counseling is normally intended particularly for borrowers deemed inherently risky, the true effect of NCDFI client counseling on improving loan performance is likely even larger than that implied by our estimates.

Our analysis does not pinpoint the mechanism through which NCDFI client counseling aids loan performance. A borrower's exposure to financial counseling presumably enhances their financial literacy and skills. Counseling also provides an opportunity for the lender to monitor the borrower. Last but not least, lender-provided counseling may serve as a signal of the lender's genuine commitment to the client, boosting the client's efforts to repay. Future research should explore why NCDFI-provided financial counseling aids loan performance.

Our conclusions are based on data collected from one prominent NCDFI. Subject to this caveat, our findings are indicative of the importance of the growing, but understudied, NCDFI industry for financial development of Indian Country. Beyond Indian Country, our analysis illustrates that in financially underdeveloped areas that have not been the focus of government policy, local private-sector organizations can themselves take productive steps to mitigate their lending risks and thereby help improve the performance of the local credit market.

References

Albanesi, S., Vamossy, D.F. 2019. Predicting consumer default: A deep learning approach. NBER working paper 26165.

Barbaglia, L., Manzan, S., Tosetti, E. 2021. Forecasting loan default in Europe with machine learning. Journal of Financial Econometrics, forthcoming.

Butaru, F., Chen, Q., Clark, B., Das, S., Lo, A.W., Siddique, A. 2016. Risk and risk management in the credit card industry. Journal of Banking and Finance 72(C), 218–239.

Cleves, M., Gutierrez, R.G., Gould, W., Marchenko, Y.V. 2010. An Introduction to Survival Analysis Using Stata: Third Edition. College Station, Texas: Stata Press.

Cornell, S., Jorgensen, M. 2022. Indigenous Nations in postracial America: Rethinking social inclusion. Review of Black Political Economy 49(2), 111–129.

Cornell, S., Kalt. J.P. 2007. Two approaches to the development of Native nations: One works, the other doesn't. In: Jorgensen, M. (ed.), Rebuilding Native Nations: Strategies for Governance and Development. Tucson, Arizona: University of Arizona Press, 3–33.

Dewees, S., Sarkozy-Banoczy, S. 2008. Investing in Native community change: Understanding the role of Community Development Financial Institutions. Washington, D.C.: U.S. Department of the Treasury, CDFI Fund.

Dimitrova-Grajzl, V., Grajzl, P., Guse, A. J., Todd, R.M. 2015. Consumer credit on American Indian reservations. Economic Systems 39(3), 518–540.

Dimitrova-Grajzl, V., Grajzl, P., Guse, A.J., Kokodoko, M. 2022. Community development financial institutions and individuals' credit risk in Indian Country. Journal of Economic Issues 56(1), 184–208.

Dimitrova-Grajzl, V., Grajzl, P., Guse, A.J., Todd, R.M., Williams, M. 2018. Racial characteristics, credit history, and bankcard credit in Indian Country. Comparative Economic Studies 60(3), 410–441.

Hastings, J.S., Madrian, B.C., Skimmyhorn, W.L. 2013. Financial literacy, financial education, and economic outcomes. Annual Review of Economics 5(1), 347–373.

Jorgensen, M. 2016. Access to Capital and Credit in Native Communities. Tucson, Arizona: Native Nations Institute.

Jorgensen, M., Taylor, J.B. 2015. New Paths Home, The Impact of Four Directions Development Corporation on Indian Island, Maine 2001-2014. Sarasota, Florida: The Taylor Policy Group.

Kokodoko, M. 2015. Growth and performance of the Native CDFI loan fund sector, 2001–2012. Federal Reserve Bank of Minneapolis Community Development Report No. 2015-1.

Kokodoko, M. 2017. Findings from the 2017 Native CDFI Survey: Industry Opportunities and Limitations. Federal Reserve Bank of Minneapolis CICD Working Paper 2017-04.

Listokin, D, Temkin, K., Pindus, N., Stanek, D. 2017. Mortgage Lending on Tribal Land: A Report from the Assessment of American Indian, Alaska Native and Hawaii Housing Needs. Washington, DC: U.S. Department of Housing and Urban Development: Office of Policy Development and Research.

Lusardi, A., Mitchell, O.S. 2014. The economic importance of financial literacy: Theory and evidence. Journal of Economic Literature 52(1), 5–44.

Table 1: Descriptive statistics, key loan and borrower characteristics

	All loans (441 obs.)		Loans of borrowers without a credit score (119 obs.)		Loans of borrowers with a credit score (322 obs.)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Loan characteristics						
Term (in months)	19.1	9.0	14.5	10.0	20.8	7.9
Interest rate (in percent)	10.7	1.9	10.5	2.5	10.7	1.7
Amount (in $)	2,495.3	1404.6	1,840.2	1,006.2	2,737.4	1,454.0
Credit-builder loan (dummy)	0.773	0.419	0.513	0.502	0.870	0.337
Hardship loan (dummy)	0.166	0.372	0.462	0.501	0.056	0.230
Holiday loan (dummy)	0.039	0.193	0.017	0.129	0.047	0.211
Other loan (dummy)	0.023	0.149	0.008	0.092	0.028	0.165
Borrower characteristics						
Male (dummy)	0.354	0.479	0.403	0.493	0.335	0.473
Age at closed deal (in years)	41.0	12.4	42.3	12.7	40.5	12.3
Not from South Dakota (dummy)	0.020	0.142	0.034	0.181	0.016	0.124
Not Native American (dummy)	0.032	0.176	0.034	0.181	0.031	0.174
At least some post-second. educ. or more (dummy)	0.585	0.493	0.672	0.471	0.553	0.498
Household size (members count)	2.9	2.1	3.2	2.0	2.8	2.2
Household income (in $)	32,229.6	26,061.2	41,138.2	28,582.3	28,937.3	24,297.5
Without credit score (dummy)	0.270	0.444	1	0	0	0
Credit score poor (dummy)	0.308	0.462	0	0	0.422	0.495
Credit score fair or better (dummy)	0.422	0.494	0	0	0.578	0.495
Credit score if credit score>0	594.1	70.6			594.1	70.6

Notes: The table reports the descriptive statistics for key loan and borrower characteristics. Credit score is poor if larger than or equal to 300 but smaller than 580. Credit score is fair or better if larger than or equal to 580. The estimation results reported in Tables 3–4 also control for the biyear of closed deal. Information on counseling hours received by borrower is presented in Table 2. "S.D." is short for "standard deviation."

Table 2: The distribution of loans by borrower exposure to counseling

All loans (441 obs.)			Loans of borrowers without a credit score (119 obs.)			Loans of borrowers with a credit score (322 obs.)		
Couns. hrs	Freq.	Cum. %	Couns. hrs	Freq.	Cum. %	Couns. hrs	Freq.	Cum. %
0	318	71.11	0	99	83.19	0	219	68.01
0.25	44	82.09	0.25	10	91.60	0.25	34	78.57
0.50	29	88.66	0.50	4	94.96	0.50	25	86.34
0.75	13	91.61	0.75	3	97.48	0.75	10	89.44
0.80	1	91.84	0.80	0	97,48	0.80	1	89.75
1.00	9	93.88	1.00	1	98.32	1.00	8	92.24
1.10	1	94.10	1.10	0	98.32	1.10	1	92.55
1.25	6	95.46	1.25	0	98.32	1.25	6	94.41
1.50	5	96.60	1.50	0	98.32	1.50	5	95.96
1.75	5	97.73	1.75	1	99.16	1.75	4	97.20
2.00	2	98.19	2.00	1	100.00	2.00	1	97.52
2.50	4	99.09	2.50	0	100.00	2.50	4	98.76
2.75	2	99.55	2.75	0	100.00	2.75	2	99.38
3.25	1	99.77	3.25	0	100.00	3.25	1	99.69
3.50	1	100.00	3.50	0	100.00	3.50	1	100.00
Mean	0.22		Mean	0.10		Mean	0.26	
S.D.	0.51		S.D.	0.29		S.D.	0.56	

Notes: The table shows the distribution of loans by counseling hours received by borrower. The left-most set of three columns shows the distribution for all loans. The middle set shows the distribution for loans of borrowers without a credit score. The right-most set shows the distribution for loans of borrowers with a credit score. The bottom two rows show the mean and standard deviation of counseling hours for each sample. “Freq.” is short for “frequency” and “Cum. %” is short for “cumulative percent.”

Table 3: Financial counseling and hazard of bad debt, Cox model

	(1)	(2)	(3)	(4)	(5)	(6)
Counseling hrs>0, without credit score	0.463+	0.239***	0.179***			
	(0.250)	(0.139)	(0.116)			
Counseling hrs=0, with credit score	0.509*	0.188***	0.135***			
	(0.196)	(0.081)	(0.063)			
Counseling hrs>0, with credit score	0.651	0.215***	0.174***			
	(0.241)	(0.098)	(0.084)			
Counseling hrs∈(0, 0.5), without credit score				1.490	0.554	0.410
				(1.028)	(0.357)	(0.328)
Counseling hrs≥0.5, without credit score				0.311*	0.163**	0.122***
				(0.191)	(0.121)	(0.095)
Counseling hrs=0, with credit score				0.523*	0.189***	0.140***
				(0.205)	(0.081)	(0.066)
Counseling hrs∈(0, 0.5), with credit score				0.926	0.300**	0.219***
				(0.381)	(0.162)	(0.126)
Counseling hrs≥0.5, with credit score				0.538	0.171***	0.152***
				(0.229)	(0.083)	(0.077)
Loan characteristics	No	Yes	Yes	No	Yes	Yes
Borrower characteristics	No	No	Yes	No	No	Yes
Bad debts	60	60	60	60	60	60
Observations (loans)	441	441	441	441	441	441
Log pseudolikelihood	-260.14	-241.34	-231.94	-258.25	-239.89	-230.95

Notes: The table shows the estimated hazard ratios (exponentiated coefficients) based on the Cox model where the failure event is loan turning into bad debt. Loan characteristics include term (in months), interest (percent), amount (logged), type (dummy for credit-builder), and year of closed deal (biyear dummies). Borrower characteristics include gender (male dummy), age at closed deal (in years), residence (dummy for South Dakota), race (dummy for non-Native American), attained education (dummy for at least some post-secondary or more), household size (member count), and household income (inverse hyperbolic sine, because sole-proprietor borrowers can have negative income). The omitted category is loans when the borrower neither received counselling nor possesses a credit score. Heteroscedasticity-robust standard errors in parentheses. ***, **, and * indicate *p*-value smaller than 0.01, 0.05, and 0.1, respectively, based on a two-sided test. + indicates *p*-value smaller than 0.1 based on a one-sided test.

Table 4: Robustness, stratified Cox and Weibull models

	Stratified Cox		Weibull	
	(1)	(2)	(3)	(4)
Counseling hrs>0, without credit score	0.210**		0.153***	
Counseling hrs=0, with credit score	0.152***		0.118***	
Counseling hrs>0, with credit score	0.220**		0.163***	
Counseling hrs∈(0, 0.5), without credit score		0.434		0.398
Counseling hrs≥0.5, without credit score		0.143**		0.105***
Counseling hrs=0, with credit score		0.154***		0.121***
Counseling hrs∈(0, 0.5), with credit score		0.257**		0.194***
Counseling hrs≥0.5, with credit score		0.194***		0.146***
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Bad debts	60	60	60	60
Observations (loans)	441	441	441	441
τ			3.20	3.25
Log pseudolikelihood	-201.55	-200.81	-90.36	-89.30

Notes: The table shows the estimated hazard ratios (exponentiated coefficients) for models where the failure event is loan turning into bad debt. Columns (1) and (2) show results based on stratified Cox model where the baseline hazard varies by loan type (credit-builder, hardship, holiday, and other). Columns (3) and (4) show results based on the Weibull model. Loan characteristics always include term (in months), interest (percent), amount (logged), and year of closed deal (biyear dummies). In columns (3) and (4), loan characteristics additionally include loan type (dummy for credit-builder). Borrower characteristics always include gender (male dummy), age at closed deal (in years), residence (dummy for South Dakota), race (dummy for non-Native American), attained education (dummy for at least some post-secondary or more), household size (member count), and household income (inverse hyperbolic sine, because sole-proprietor borrowers can have negative income). The omitted category is loans when the borrower neither received counselling nor possesses a credit score. τ is an ancillary parameter of the Weibull distribution, with value larger than 1 indicating increasing hazard. Heteroscedasticity-robust standard errors not reported. ***, **, and * indicate *p*-value smaller than 0.01, 0.05, and 0.1, respectively, based on a two-sided test.

Figure 1: Probability that loan is declared bad debt, non-parametric estimates