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Abstract

We examine whether concerns about lenders' discrimination based on community racial characteristics can be empirically substantiated in the context of neighborhoods on and near American Indian reservations. Drawing on a large-scale dataset consisting of individual-level credit bureau records, we find that residing in a predominantly American Indian neighborhood is ceteris paribus associated with worse bankcard credit outcomes than residing in a neighborhood where the share of American Indian residents is low. While these results are consistent with the possibility of lenders' discrimination based on community racial characteristics, we explain why our findings should not be readily interpreted as conclusive evidence thereof. We further find that consumer's credit history is a robust and quantitatively more important predictor of bankcard credit outcomes than racial composition of the consumer's neighborhood, and that the consumer's location vis-à-vis a reservation exhibits no effect on bankcard credit outcomes.

JEL-Codes: G210, J150, P430, R110.

Keywords: bankcard credit, American Indian reservations, discrimination, neighborhood racial characteristics, credit history.

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1. Introduction

Credit cards are the most widely available form of consumer credit in the United States. The majority of American households have at least one credit card, most often a bank-issued general purpose card, or bankcard. Over 70 percent of households regularly make payments with credit cards (Schuh and Stavins 2014), nearly 40 percent use credit cards to borrow in a typical month (Bricker et al. 2014), and about 65 percent applied for a credit card in a typical recent year (Larrimore et al. 2015). Bankcards are often a vehicle through which young consumers establish a credit history that opens the door to homeownership (Debbaut et al. 2014). Bankcards and the credit they provide are thus a consumer mainstay, facilitating transactions, consumption smoothing, household financial risk management, and, for many small-scale entrepreneurs, business finance.

Given the value of bankcards to consumers, it is not surprising that policymakers have intervened to try to ensure fair access to this type of credit.[1] Yet despite these interventions, concerns persist about unequal access to and usage of bankcards in minority communities (see, e.g., Skanderson and Ritter 2014).[2] Because publically available data on individuals' access to and usage of credit cards are limited to the Survey of Consumer Finance (SCF) and a few other small, nationally (but not regionally) representative surveys, systematic research on the topic is scant.

[1] For example, according to the Consumer Financial Protection Bureau, the Equal Credit Opportunity Act of 1974 "does not guarantee that you will get credit. You must still pass the card issuer's tests of creditworthiness. But the law bars discrimination based on age, sex, marital status, race, color, religion, and national origin in deciding whether to extend credit to an applicant, in deciding the terms (such as the interest rate or credit limit), or in any other aspect of a credit transaction. The law also generally bars discrimination because you receive public assistance income, or because you exercise your rights under certain federal credit laws (such as filing a billing dispute with a card issuer)" (http://www.consumerfinance.gov/askcfpb/19/what-information-are-card-issuers-not-allowed-to-base-decisions-on-when-considering-a-credit-card-application.html). Credit cards are among the covered types of credit. See also Skanderson and Ritter (2014).

[2] In a recent major federal credit card discrimination settlement, the GE Capital Retail Bank was accused of deceptive marketing and discrimination against Hispanics. The Consumer Financial Protection Bureau and Department of Justice ordered GE Capital to pay $225 million in relief. See http://www.justice.gov/opa/pr/justice-department-and-consumer-financial-protection-bureau-reach-169-million-settlement.

Using data from the 2010 SCF, Firestone (2014: 1206) shows that "after controlling for many factors…Blacks and Hispanics are both less than half as likely as others to have at least one credit card", a finding consistent with an analysis of earlier SCF data by Bertaut and Haliassos (2006). Firestone (2014: 1206) further analyzes proprietary data on mailed credit card offers and finds "unexplained discrepancies in credit card marketing to Black and Hispanic consumers". Using similar data from mailings, Han et al. (2013) find that white consumers are more likely to receive a credit card offer and to be offered favorable terms than minority consumers with comparable risk profiles. They also find that the odds of receiving an offer are higher for consumers in areas with a relatively strong economy and pro-creditor legal system. Cohen-Cole (2011) and Brevoort (2011) use proprietary credit history data to examine discrimination by neighborhood racial characteristics (so-called *redlining*). Cohen-Cole (2011) reports evidence that credit card issuers systematically gave residents of African-American neighborhoods lower credit limits than they gave to individuals with similar financial credentials living in similar, but non-African-American, neighborhoods. Brevoort (2011), however, raises a series of methodological concerns about Cohen-Cole's (2011) approach and demonstrates the lack of robustness of Cohen-Cole's findings.

Similar concerns have been raised about access to and usage of consumer credit, including bankcards, for American Indians and American Indian communities—"America's domestic emerging market" (Clarkson 2009: 287)—for which research has been particularly scarce even though undersupply of credit had been identified as a key obstacle to economic progress of American Indian reservations (see, e.g., Community Development Financial Institutions Fund 2001, Parker 2012, Brown et al. 2015).[3] Using SCF data, Crook (1996: 482) groups American Indians with Asians and others, and finds that "the probability that a household is credit-rationed

[3] For references to empirical studies on various aspects of economic development in Indian Country, see Section 1 in Dimitrova-Grajzl et al. (2015).

increases if the head of household is Black or American Indian/Eskimo/Aleut/Asian rather than White". Since credit cards are the most widespread form of consumer credit, Crook's (1996) finding that American Indians may be subject to overall consumer credit rationing suggests they likely have limited access to bankcards as well. In their recent analysis of consumer credit on or near American Indian reservations, Dimitrova-Grajzl et al. (2015) use the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) data aggregated at the Census block group-level to show that usage of some types of credit is lower within reservations (based on simple correlations) and areas with a high percentage of American Indian residents (after controlling for an array of factors). Among the types of credit with lower usage identified by Dimitrova-Grajzl et al. (2015) is unsecured consumer credit, including bankcard credit.[4]

In this paper, we likewise draw on the CCP data, but in contrast to Dimitrova-Grajzl et al. (2015) examine the determinants of *individual-level bankcard credit outcomes* in the neighborhoods on and near American Indian reservations (also known as Indian Country). Much like Tootell (1996), Campbell et al. (2008), Cohen-Cole (2011), and Brevoort (2011), we are particularly interested in the impact of *neighborhood racial characteristics* on individuals' credit outcomes. Unlike the existing literature, however, we examine whether concerns that bankcard issuers make lending decisions based on the racial composition of the borrower's neighborhood—an act that would constitute "a clear violation of the Equal Credit Opportunity Act" (Brevoort 2011: 714)—can be empirically substantiated *in the context of Indian Country*. To this end, we use a series of reduced-form empirical models and employ a wide range of individual and neighborhood level controls as well as fixed effects to explore if bankcard outcomes for

[4] Earlier assessments of redlining of non-mortgage consumer credit on reservations, using interviews and reports from local experts, include Pickering and Mushinski (1999) and Community Development Financial Institutions Fund (2001).

individuals who reside in Indian Country neighborhoods with a high share of American Indian residents all else equal differ systematically from bankcard outcomes for individuals who reside in Indian County neighborhoods with a lower share of American Indian residents.

Our main findings may be briefly summarized as follows. First, relative to residing in an Indian Country neighborhood with a low share of American Indians, residing in an Indian Country neighborhood with a high share of American Indian residents is, after controlling for a wide range of factors, associated with statistically significantly lower bankcard credit limits; lower prospects of obtaining a bankcard; and higher likelihood of being late on bankcard debt repayment. These results are consistent with the possibility that bankcard issuers in Indian Country discriminate based on neighborhood racial composition. However, due to the well-known limitations of reduced-form approaches to studying discrimination in credit markets (see, e.g., Maddala and Trost 1982, LaCour-Little 2001, Rachlis and Yezer 1993, Yezer et al. 1994, Dawkins 2002, Yezer 2010, Brevoort 2011), our findings cannot be viewed as conclusive evidence in support of the discrimination hypothesis. We explain why and how this important caveat applies in the context of our data and analysis.

Second, an individual's credit history, as captured by an individual's Equifax Risk Score and recent history of bankruptcy, overall exhibits an economically large and robustly statistically significant effect on individuals' bankcard credit outcomes. This finding suggests that despite the many institutional and developmental specifics that differentiate Indian Country from the rest of the U.S. (see, e.g., Pommersheim 1989, Cornell and Kalt 2002, Jorgensen 2007), the generally applicable result about the crucial importance of an individual's credit history for future credit outcomes (see, e.g., Gross and Souleles 2002a, 2002b; Avery et al. 2010) fully extends to the neighborhoods on and near American Indian reservations.

Third, an individual's location vis-à-vis a reservation does not matter for any of the bankcard credit outcomes we examine. This result resonates with the findings of Dimitrova-Grajzl et al. (2015), who use geographically aggregated data, for various categories of consumer credit. It further suggests that *if* lenders in Indian Country do make lending decisions based on certain characteristics of the borrower's neighborhood—a conclusion which, we emphasize, would be premature to draw based on available evidence—then the consumer's location relative to a reservation does not seem to be among them.

The rest of the paper is organized as follows. Section 2 introduces the data. Section 3 develops a theoretical framework, articulates the empirical strategy, and presents and discusses the results for bankcard credit limits. Section 4 examines the results for two further important bankcard outcomes: credit access and delinquency. Section 5 concludes.

2. Data[5]

To examine bankcard credit outcomes in Indian Country, we draw on the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP). The CCP is an anonymous, nationally representative sample of the credit history files of U.S. residents. We draw on the CCP primary files which cover about 12 million randomly chosen consumers.[6] Lee and van der Klaauw (2010) assess the representativeness of the CCP with respect to the full population of adults by comparing the data in the 2008 CCP primary files with corresponding estimates from the 2008 American Community Survey for select geographies and from the Survey of Consumer Finance. Their

[5] This section draws heavily on the analogous section in Dimitrova-Grajzl et al. (2015).
[6] The full CCP further includes additional householder files for non-randomly selected individuals who have the same address as a randomly selected individual.

findings suggest that the CCP is generally representative of the U.S. population of adults aged 20 or more and their credit usage.[7]

The credit information in the CCP is extensive. For each consumer in the sample, the CCP reports their total number of bankcards, the total credit limit and balance owed on those cards, and the total amount of bankcard balances by repayment status. Credit files with sufficient credit performance history include an Equifax Risk Score, which ranges from 280 to 850, with a lower score indicating a higher level of estimated credit risk. The CCP further provides a code for the Census block of the address that the bureau assigns to each file; this information enables us to combine CCP data with Census data (see below). While the CCP also includes the consumer's year of birth, it provides no other demographic information. In particular, the CCP does not include information about individual's race and income. The CCP also does not report any information about the contractual terms of consumer's debt or the lenders.

To study bankcard credit outcomes in Indian Country, we analyze CCP data for individuals residing on or near American Indian reservations during the years 2002-2007. We chose the first quarter of year 2002 as the beginning period for our sample because the CCP is geographically less precise prior to that (Wardrip and Hunt 2013). We selected the last quarter of year 2007 as the end period of our sample because starting from 2008 the financial turmoil and subsequent policy responses significantly changed the credit environment (see, e.g., Jambulapati and Stavins 2014). Furthermore, the chosen end period reflects the fact that we combine CCP individual-level data with year 2000 Census data on the neighborhoods in which individuals reside. The smallest

[7] However, there are caveats with respect to the representativeness of the CCP for reservation populations. First, the percentage of adults with no credit file or thin credit file may be higher on reservations, given widespread reports that credit is hard to access there. Second, Lee and van der Klaauw (2010) do not examine small rural geographies and thus provide no direct assessment of the accuracy of address information (and thus the accuracy of the CCP's Census block data) for these geographies. Third, accurate address information also could be problematic for reservations that include a large share of seasonally or intermittently mobile households moving frequently between the reservation and regional urban areas.

neighborhood for which we have Census data is the Census block.[8] At this level of geographic detail we have data on total population and population by race. Census block boundaries never cross reservation boundaries. We can thus unambiguously assign blocks to reservations or to nearby non-reservation areas. We use block population data to compute the percentage of the adult (18 or older) population that self-identifies as American Indian either as a single race or in combination with other races.

We examine credit files for about 1.3 million consumers who reside in one of the 246,177 Census blocks that lie within 10 miles (16 km) of any of the 315 Indian reservations in the U.S.[9] Table 1 provides variable descriptions for our outcome variables (panel A) and key explanatory variables (panel B). Table 2 presents basic descriptive statistics for our key explanatory variables for two out of four samples that we use in our regression analysis (see Sections 3 and 4). The relatively low share of American Indian residents (between 2.4 and 3.4 percent) associated with an observation (consumer in a given quarter) drawn randomly from one of our samples is consistent with the analogous block group-level aggregated statistic reported by Dimitrova-Grajzl et al. (2015: Table 2) and reflects the fact that many of the near-reservation blocks included in our sample are located in densely populated urban areas with a low share of American Indian residents. Table 3 present descriptive statistics for all four of our outcome variables. We measure other

[8] The entire U.S. has been divided into Census blocks, which are the smallest geographies for which Census data are routinely published. Census blocks have an average population of about 28 people, but this ranges from zero in millions of rural blocks to hundreds in some urban blocks. While in urban areas blocks are often city blocks bounded by city streets, in rural areas blocks may be much larger in area.

[9] An Indian reservation for our purposes is any area in the United States with a tribal area Census code between 1 and 4999 and at least some land recognized by the Census as reservation land. This excludes tribal statistical areas (e.g., Oklahoma Tribal Statistical Areas and State Designated Tribal Statistical Areas) which are assigned tribal area Census codes above 5000. It also leaves out 6 tribal areas whose codes have values below 5000 but whose territory consists entirely of trust land (e.g., "Minnesota Chippewa Trust Land": Census code 2285). Finally, we exclude consumers located in Alaska and Hawaii. For further information on the geographies we use, see Dimitrova-Grajzl et al. (2015).

demographic and economic characteristics of neighborhoods at the Census block group level.[10] We include block group-level Census controls, listed and defined in Table A1, in several of our regressions to mitigate omitted variable bias in our estimates of neighborhood racial composition effects (see Sections 3 and 4). However, because the effects of these controls are not of direct interest in themselves, we neither present nor discuss our estimates of the respective coefficients.

3. Effects on Credit Limits

3.1. Theoretical Framework and Empirical Considerations

The empirical models of credit volume we estimate in Section 3.2 are all reduced form. To explain our approach, we present a simple static framework of credit supply and demand. Let C^D denote consumer's demand for bankcard credit as captured, for example, by the credit limit amount on the consumer's bankcard. Suppose that

$$C^D = \alpha^D \times r + \beta^D \times AI + \mathbf{x}^D \boldsymbol{\gamma}^D + \varepsilon^D, \tag{1}$$

where C^D is the quantity of credit demanded and r is the interest rate. AI captures the racial composition of the Indian Country neighborhood in which the individual resides as measured by the share of American Indian residents. $\mathbf{x}^D$ is a row vector of other variables affecting individual's credit demand and ε^D is the error term. α^D and β^D are demand parameters and $\boldsymbol{\gamma}^D$ is a column vector of demand parameters. Similarly, suppose that card issuer's supply of bankcard credits C^S can be expressed as

$$C^S = \alpha^S \times r + \beta^S \times AI + \mathbf{x}^S \boldsymbol{\gamma}^S + \varepsilon^S, \tag{2}$$

[10] Block groups generally aggregate dozens of blocks and typical have a population of 600 to 3,000 individuals. However, their boundaries can and do cross reservation boundaries, so that some block groups may lie partly in and partly out of a given reservation.

where C^S is the quantity supplied, $\mathbf{x}^S$ is a row vector of variables other than *AI* that affect credit supply, and ε^S is the error term. α^S and β^S are supply parameters and $\boldsymbol{\gamma}^S$ is a column vector of supply parameters.

Ideally, we would be able to estimate the structural parameters of the supply equation (2) using a simultaneous equations approach. However, limitations of our data render such approach infeasible for two major reasons. First, plausible demand-specific variables, which would allow for identification of structural supply parameters, are not readily available. Second, even if plausible demand-specific variables were available, we do not observe the interest rate in our data. This obfuscates the interpretation of the structural supply parameters of interest within the postulated market-clearing demand-and-supply framework.

We, therefore, proceed as follows. Upon solving (1) for *r*, imposing the market-clearing condition (C^D=C^S=C), and substituting the resulting expression in (2), we obtain the following reduced-form expression that characterizes the equilibrium credit volume:

$$C = \beta \times AI + \mathbf{x}^D \boldsymbol{\gamma}_1 + \mathbf{x}^S \boldsymbol{\gamma}_2 + \varepsilon, \tag{3}$$

where

$$\beta \equiv a^S \beta^D - a^D \beta^S, \tag{4a}$$

$$a^S \equiv \tfrac{\alpha^S}{\alpha^S - \alpha^D}, \tag{4b}$$

$$a^D \equiv \tfrac{\alpha^D}{\alpha^S - \alpha^D}, \tag{4c}$$

$$\boldsymbol{\gamma}_1 \equiv a^S \boldsymbol{\gamma}^D, \tag{4d}$$

$$\boldsymbol{\gamma}_2 \equiv -a^D \boldsymbol{\gamma}^S, \tag{4e}$$

and $\varepsilon \equiv a^S \varepsilon^D - a^D \varepsilon^S$ is the error term. That is, the observed equilibrium volume of credit depends on a mixture of supply and demand factors and parameters. For example, the coefficient β on the neighborhood racial composition variable in the reduced-form expression (3) is, in general, a non-linear function of structural supply and demand parameters (see (4a), (4b), and (4c)). Thus, without additional information or assumptions, a negative estimate of β, for example, cannot be interpreted as providing evidence in favor of lenders' discrimination based on neighborhood racial characteristics. This is a well-known difficulty with the type of reduced-form equations we estimate (see, e.g., Yezer 2010). Further difficulties in interpreting parameter estimates of reduced-form expression (3) arise if data on some of the demand or supply factors are missing. Unless the omitted variables are uncorrelated with neighborhood racial composition, the omitted variables bias the estimated reduced-form coefficient β, thereby further clouding its interpretation.

Reduced form estimates based on (3) nevertheless provide valuable information about possible values of structural parameters. The wide range of individual and neighborhood level credit supply and demand controls and the fixed effects that we include among explanatory variables in our regression models (see Section 3.2) mitigate the omitted variable bias concerns discussed above. The implications about a specific structural supply parameter of interest may then be deduced on the basis of reduced-form estimates of parameters in (3) under specific assumptions about the likely sign and magnitude of other structural parameters that the reduced-form parameters functionally depend on (see (4a)-(4e)). We return to examples of this reasoning in Section 3.3 below when we discuss possible interpretations of our results.

Finally, we note that while the framework developed above applies most directly to our credit volume regressions with credit limit as a continuous outcome variable, the framework can, with suitable modifications, be generalized (see, e.g., LaCour-Little 2001) to motivate our credit access regressions in Section 4, where we examine the determinants of whether or not an individual obtains a bankcard. The main caveats associated with the interpretation of reduced-form credit limit regressions, where the outcome variable is continuous, therefore extend to our reduced-form credit access regressions, where the outcome variable is binary. We provide a motivation for our delinquency regressions in Section 4.

3.2. Empirical Strategy and Results

We use two different outcome variables and several different specifications to estimate the reduced-form equation of credit volume. Below, we in turn present each outcome variable as well as the associated estimation strategy and the results. We turn to a broader discussion of our findings in Section 3.3.

3.2.1. First Outcome Variable

To define our first outcome variable, we consider individuals currently without a bankcard who obtain one or more bankcards in the next quarter. We use as the outcome variable the natural log of an individual's total credit limit on the new bankcards (*First Credit Limit*). So-defined first awarded bankcard credit limit is by definition independent of recent bankcard usage, and, hence, recent bankcard demand considerations.[11] The outcome variable *First Credit Limit* thus mitigates the problems associated with interpreting our reduced-form regression results as capturing credit supply rather than credit demand.[12]

Our key explanatory variable of interest captures the racial composition of the neighborhood in which an individual resides and is defined as the share of adult population in a Census block that identifies as American Indian. At the individual level, we, first, control for an

[11] Note that the sample of consumers for whom First Credit Limit is defined involves two types of consumers: those who have previously never possessed a bankcard (and for whom the credit limit awarded on the new bankcards is therefore really the 'first' credit limit) and those who had previously possessed a bankcard but currently do not possess one.

[12] Brevoort (2011: 723) for example argues that "aggregate credit limits will depend heavily on the number of credit cards…a person chooses to maintain (subject, of course, to the willingness of lenders to extend credit), and this will depend on both demand and supply effects….For example, an individual's decision to close a credit line will decrease aggregate credit limits not as a result of a supply shock but because of a decision made by the consumer."

individual's Equifax Risk Score by including a full set of indicator variables for deciles of the Equifax Risk Score distribution based on our full sample. This method of controlling for the relative magnitude of an individual's Equifax Risk Score allows for non-linear effects and is intended to minimize any bias arising from functional form misspecification (see, e.g., Han et al. 2013). Second, for the same reason, we control for individual's age via inclusion of a full set of age dummies. Third, to control for any additional effect of an individual's credit history potentially not captured by individual's Equifax Risk Score, we control for the history of recent bankruptcy filings. Han et al. (2013), for example, show that in their data consumer's bankruptcy history indeed impacts credit card offers. We differentiate between Chapter 7 and Chapter 13 bankruptcy filings because the two may exhibit different effects on consumer's credit outcomes. Since Chapter 13 filings do not result in the discharge of all debts, but rather involve a restructuring of payments, creditors would likely treat a consumer with a Chapter 13 filing in their past differently from a consumer with a Chapter 7 filing. We further allow for time since recent Chapter 7 or Chapter 13 bankruptcy filing to exhibit a potentially non-linear effect.

In order to mitigate the confounding effect of any time-varying unobserved factors which may affect bankcard credit limits and, at the same time, correlate with our Census block-level measure of racial neighborhood composition, we include different sets of fixed effects. In the first subset of specifications, we control for *county-by-quarter* fixed effects that absorb any effects at the geographic level of a county that vary over time, such as for example county-level business cycle effects. County-by-quarter effects further absorb changes in the price level which allows us to interpret our effects as real (rather than nominal).

In all regression specifications with county-by-quarter effects, we control for an individual's location relative to a reservation to examine whether reservation borders per se have an effect on credit outcomes. Specifically, we use indicator variables for whether a block lies on a reservation or is adjacent to a reservation, with blocks within ten miles of but not adjacent to a reservation serving as the omitted category.[13] In a further subset of specifications with county-by-quarter effects, we additionally include a wide range of socio-economic controls utilized by Cohen-Cole (2011) and Brevoort (2011). These variables are measured at the block group level and based on the 2000 Census (see Table A1).

In the second subset of specifications, we instead include *block group-by-quarter* fixed effects. Inclusion of block group-by-quarter effects has the advantage over inclusion of county-by-quarter effects by controlling for time-varying factors at a finer geographic level and, at the same time, allows for variation in our racial neighborhood composition variable (which is measured at the smaller, block level). Reservation borders align nearly perfectly with block group borders. Thus, some salient reservation-level factors, which may influence credit outcomes and which our block group-by-quarter effects control for, include reservation land ownership features such as the extent of trust land (see, e.g., Anderson and Lueck 1992, Laderman and Reid 2010, Akee and Jorgensen 2014) and the degree of land ownership fractionation (see, e.g., Russ and Stratmann 2014), tribal culture and governance (see, e.g., Cornell and Kalt 2000, Pickering and Mushinski 2001, Dippel 2014, Akee et al. 2012), the presence or absence of casinos (see, e.g., Evans and Topoleski 2002, Cookson 2010, Anderson 2013), the allocation of jurisdiction over disputes (see, e.g., Parker 2012, Dimitrova-Grajzl et al. 2015, Brown et al. 2015) as well as access

[13] The correlation between the variables *Share American Indian* and *On Reservation* is positive, but not extremely high and varies across the samples we draw on in our analysis: it equals 0.61 in the *First Credit Limit* sample examined below and is as low as 0.48 in the *90 Days Past Due* sample (see Section 4). The correlation between the variables *Share American Indian* and *Adjacent to Reservation* is very low and never exceeds 0.02 in any of the samples we use. The variables *Share American Indians*, *On Reservation*, and *Adjacent to Reservation* therefore exhibit sufficient independent variation to examine the effect of reservation borders while controlling for the effect of neighborhood racial composition. In addition, we also report results based on specifications where we omit controlling for neighborhood racial composition and replace county-by-quarter effects with state-by-year effects to allow for ample variation in neighborhood's location relative to a reservation within a given geographic unit.

to banks and reservation-specific financial lending institutions such as Native Community Development Financial Institutions (see Dimitrova-Grajzl et al. 2015). Given the lack of an individual-level control for income in our data, a further important advantage of the inclusion of block group-by-quarter effects instead of county-by-quarter effects is that the former proxy for individual income better than the latter.

The disadvantage of controlling for block group-by-quarter effects is that the variation in block-level racial neighborhood composition within block groups may be relatively small in many block groups and, hence, inclusion of block group-by-quarter fixed effects limits the extent of variation that we are able to rely on to estimate the effect of our key explanatory variable of interest.[14] Moreover, since reservation borders almost perfectly align with block groups, when we include block group-by-quarter fixed effects we purposefully do not control for an individual's location relative to a reservation.

Finally, we briefly comment on the standard errors that we use for statistical inference. All of our standard errors are heteroskedasticity-robust. In addition, they are clustered to allow for non-zero correlation between error terms for observations within the same cluster (but not across clusters). Our definition of a cluster, however, for reasons of computational feasibility varies across our specifications. Specifically, to ensure an appropriate number of degrees of freedom in the estimation of clustered standard errors, our definition of a cluster coincides with the notion of fixed effects that we include in our regression specification.[15] Thus, in specifications with county-by-quarter fixed effects we cluster standard errors at the level of county-by-quarter, and in

[14] There are on average about 15 Census blocks in a randomly selected Census block group in our sample. Census block groups with less than five Census blocks represent about 12 percent of all Census block groups in our sample.
[15] More generally, we would prefer to cluster at a higher (say, county) level. However, usage of Stata's areg command requires that "the number of levels of the absorb() variable should not exceed the number of clusters" (see http://www.stata.com/manuals13/rareg.pdf).

specifications with block group-by-year effects we cluster standard errors at the level of block group-by-year.

The results are presented in Table 4. The coefficient on the neighborhood racial composition variable (*Share American Indian*) is negative in all three reported specifications and statistically significant in the specifications with county-by-quarter fixed effects (columns (1) and (2)). Controlling for block group level socio-economic variables (column (2)), which include income, more than halves the coefficient estimate. Based on the estimates in column (2), consumers residing in neighborhoods where all residents are American Indians are all else equal on average awarded a 10.8 percent lower total credit limit than consumers who reside in neighborhoods with no American Indian residents.

Replacing county-by-quarter effects and time-invariant block group level Census controls with finer block group-by-quarter effects additionally decreases the magnitude of the estimated coefficient on the neighborhood racial composition variable and renders the coefficient statistically insignificant. Recall that one possible explanation for the lack of statistical significance of the effect of neighborhood racial composition in column (3) is the fact that, due to the limited number of Census block in a typical Census block group, upon inclusion of Census block group-by-year fixed effects the Census block-level share of American Indians exhibits limited variation.

Once controlling for neighborhood racial composition, we also do not find any statistically significant effect of an area's geographic location vis-à-vis a reservation (see columns (1) and (2)). The lack of an effect of reservation borders on the awarded credit limit amount resonates with the findings of Dimitrova-Grajzl et al. (2015) and is robust to omitting the racial neighborhood composition variable and replacing the county-by-quarter effects with state-by-year effects (not reported).[16]

In contrast, the variables capturing an individual's credit history are overall statistically highly significant across all three specifications reported in Table 4. To interpret the coefficients on the Equifax Risk Score decile dummies, note that the omitted category is the lowest (first) decile. Thus, based on specification in column (3), for example, possessing Equifax Risk Score in the fifth as opposed to the lowest decile of the Equifax Risk Score distribution is all else equal associated with, on average, a 154 percent increase in total awarded bankcard credit limit. Possessing Equifax Risk Score in the highest as opposed to lowest decile of the Equifax Risk Score distribution is all else equal associated with on average a 877 percent increase in total awarded bankcard credit limit. Possessing Equifax Risk Score in the second decile of the distribution, however, is somewhat surprisingly associated with a slightly *lower* credit limit than possessing Equifax Risk Score in the lowest (first) decile. One plausible explanation for this non-monotonic effect of the Equifax Risk Score is that, consistent with the assessment of an industry expert with whom we shared our findings, a disproportionate share of consumers in the lowest (first) decile of the Equifax Risk Score distribution receive so-called secure cards.[17] Because holders of secured cards deposit money with the bankcard issuer as collateral for the bankcard, such consumers may all else equal be granted a higher credit limit than the consumers with a marginally better credit history (those with Equifax Risk Score in the second decile of the distribution) but who are not holders of a secure card.

[16] All of the mentioned results labeled as 'not reported' are available upon request.

[17] Secured cards are often attractive to people with very poor credit histories either because they want to establish a more complete or more positive credit history, or because they want the convenience of online and other card purchases.

Interestingly, even after controlling for an individual's Equifax Risk Score, recent history of personal bankruptcy is statistically significantly negatively associated with total awarded credit limit across all specifications in Table 4. Based on the estimates in column (3), having filed for Chapter 7 bankruptcy within the last three years is associated with, on average, a 22 percent decrease in the total awarded bankcard credit limit. The negative effect of Chapter 7 bankruptcy on the total awarded credit limit is smaller (17 percent) if the consumer filed for bankruptcy between four and six years ago, and disappears if the consumer filed for Chapter 7 bankruptcy seven to nine years ago.[18] The effect of filing for Chapter 13 bankruptcy is very similar in terms of the duration of the effect as well as the magnitude. These findings suggests that filing for personal bankruptcy has a lingering effect on an individual's credit limit beyond the effect captured by the Equifax Risk Score.

3.2.2. Second Outcome Variable

The second outcome variable that we use to measure an individual's credit limit uses all individuals in our sample and is defined as the natural log of an individual's total credit limit summed across all bankcard accounts in the next quarter (*Next Credit Limit*). This dependent variable facilitates the empirical strategy where we control for individual fixed effects and aim to identify the effect of neighborhood's racial composition on the individual's credit limit off of individuals who changed their location from one Census block to another. Any instance of change in an individual's Census block location provides within-individual variation in neighborhood's racial composition.[19]

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[18] After nine years, personal bankruptcy is no longer part of the credit file.

[19] We combine the reliance on individual fixed effects with the outcome variable *Next Credit Limit* rather than *First Credit Limit* discussed in Section 3.2.1 above because usage of the latter by definition restrict the sample to individuals currently without a bankcard, which already very notably reduces the sample size. With inclusion of individual fixed effects, identification of the effect of neighborhood characteristics would therefore necessarily rely on a limited number of movers.

There are more than 440,000 instances of moves that include a change in an individual's Census block location in our sample.[20]

We again include the same set of explanatory variables capturing the neighborhood's racial composition, an individual's Equifax Risk Score decile, age, and years since last bankruptcy as discussed in Section 3.2.1 above. Unlike the specifications discussed in Section 3.2.1, we replace county-by-quarter or block group-by-quarter effects with *individual* fixed effects and quarter effects. Individual fixed effects control for any individual-specific time-invariant factors which might affect credit supply and demand. Individual fixed effects therefore absorb any effect of an individual's race (which is in fact unobservable to bankcard issuers) as well as proxy for individual's projected medium-run income. Individual fixed effects, however, are not able to capture short-term fluctuations in individual's income, which likely affect an individual's decision to move.[21] As a consequence, our reduced-form estimates may still be susceptible to an omitted variable bias.

We include quarter effects to control for the impact of any time-varying economy-wide factors and to interpret our effects as real (as opposed to nominal). As changes in the awarded bankcard credit limit tend to occur periodically (rather than on an on-going basis), we additionally control for the time since we observe the individual's last credit limit change and the sign of the last credit limit change (see Table A2). In one specification, we further include the full set of socio-economic controls measured at the level of a Census block group, as noted in Section 3.2.1 above.

[20] There are more than 250,000 individuals (out of more than 820,000) who move at least once in our sample.

[21] Data are indeed consistent with this conjecture. In our sample, moves to areas with a significantly higher share of American Indian residents are accompanied by an average five percent *decrease* in Census block group-level median housing value while moves to areas with significantly lower share of American Indian residents are associated with an average seven percent *increase* in Census block group-level median housing value.

We base statistical inference on heteroskedasticity-robust standard errors, clustered at the level of an individual, in all of the regressions discussed in this subsection.

The results are presented in Table 5. The estimate of the coefficient on the neighborhood racial composition variable is negative and statistically significant in both reported specifications. Relative to the specification without Census block group level controls (column (1)), inclusion of these controls (column (2)), which include block group measure of income, further reduces the magnitude of an already small point estimate of the coefficient on the neighborhood racial composition variable. Based on the estimates in column (2), consumers residing in neighborhoods where all residents are American Indians are all else equal awarded on average a 3.8 percent lower total credit limit than consumer who reside in neighborhoods with no American Indian residents. Much like in the *First Credit Limit* regressions (see Section 3.2.1), we do not find an effect of an area's geographic location vis-à-vis a reservation.

The variables capturing an individual's credit history are overall statistically highly significant in both specifications reported in Table 5. An Equifax Risk Score in the sixth or higher, as opposed to first, decile of the distribution is associated with a higher awarded total credit limit. The implied magnitude of the effect (based on the estimates in column (2), 7.1 percent for Equifax Risk Score in sixth versus first decile and 15.9 percent for Equifax Risk Score in tenth versus first decile) is notably smaller than the effect based on the *First Credit Limit* regressions (see Table 4), a discrepancy that we attribute to the inclusion of individual fixed effects in the *Next Credit Limit* regressions. However, possessing Equifax Risk Score in the second to fifth decile of the distribution is associated with somewhat *lower* credit limit than possessing Equifax Risk Score in the lowest (first) decile. In addition to the argument, suggested in Section 3.2.1, that consumers with the lowest Equifax Risk Scores are very likely offered secure cards, a further possible explanation for this non-monotonic effect of the Equifax Risk Score, suggested to us by a bankcard industry expert, is that there exists a nontrivial number of individuals in our sample who obtained high limits and borrowed large amounts before experiencing an unfavorable event that caused their Equifax Risk Score to fall sharply and also made it difficult or unattractive to pay down their high bankcard balance. In those cases, the current credit card limit reflects the large balance previously incurred and still outstanding rather than the limit the bankcard issuer would prefer to set in light of the borrower's deteriorated performance. We have verified that this empirical pattern—typical bankcard credit limits being higher in the lowest Equifax Risk Score decile than in the next few higher deciles—indeed holds not only in our sample but also in the CCP generally.

As in the case of *First Credit Limit* results discussed in Section 3.2.1, a recent history of bankruptcy is associated with lower awarded total credit limit as measured by *Next Credit Limit* even after controlling for the relative magnitude of an individual' Equifax Risk Score. The negative effect of bankruptcy on total awarded credit limit is even larger in magnitude than the effect when we use the *First Credit Limit* outcome variable and do not control for individual fixed effects. Moreover, the estimates in Table 5 suggest that the adverse effect on total awarded credit limit persists even seven to nine years after filing for either Chapter 7 or Chapter 13 bankruptcy.

3.3. Discussion

Our results in Sections 3.2.1 and 3.2.2 indicate that neighborhood racial composition exhibits a fairly robustly negative effect on the credit limits awarded to consumers in Indian country. When using *First Credit Limit* as the outcome variable, the coefficient on the racial composition variable is negative but notably decreases in size when controlling for time-invariant socio-economic characteristics (including income) at the block group-level and becomes statistically insignificant once controlling for block group-by-quarter effects. For *Next Credit Limit* outcome variable, the coefficient on the racial composition variable is negative and statistically significant in both specifications. The variables capturing an individual's credit history are statistically significant across all specifications and imply economically large effects of Equifax Risk Score and personal bankruptcy on the observed credit limits.

What do our reduced-form results imply about the effect of racial neighborhood characteristics and individual's credit history for supply of credit in Indian country? Several prior contributions to the credit literature (e.g., Gross and Souleles 2002, Coibion et al. 2014, Bertaut and Haliassos 2006) adopt the perspective that credit limits primarily reflect supply decisions. Partly on that basis, Cohen-Cole (2011) argued that reduced-forms similar to our credit limit regressions may be interpreted as capturing the factors that determine the supply of bankcard credit. Drawing on the framework developed in Section 3.1 and following the reasoning of Brevoort (2011), who criticized Cohen-Cole's (2011) approach, as well as critics of single-equation models of discrimination more generally (e.g., Maddala and Trost 1982, LaCour-Little 2001, Rachlis and Yezer 1993, Yezer, Phillips and Trost 1994, Dawkins 2002, Yezer 2010), we argue that the interpretation of reduced-form estimates of the determinants of credit limits requires much caution. In particular, even in the absence of omitted variables that may further obscure our reduced-form estimates, the coefficients on our explanatory variables of interest are, in general, non-linear functions of structural supply and demand parameters (see Section 3.1). As such, they do not readily lend themselves to an interpretation as supply parameters.

To illustrate this point in the context of our results, consider the coefficient on the neighborhood racial composition variable in our reduced-form estimates of credit limits. The point estimate of the coefficient is negative across all specifications and statistically significantly different from zero in four out of five specifications (see Tables 4 and 5). Basic laws of demand

and supply imply that α^D<0 and α^S>0 (see expressions (1) and (2)). It follows that a^S>0 and a^D<0 (see (4b) and (4c)). Based on expression (4a), therefore, β may be negative for two distinct reasons. Suppose, first, that β^D in expression (1) is non-negative: all else equal, residing in a predominantly American Indian neighborhood in Indian country either has no effect on demand for bankcards or residents of predominantly American Indian neighborhoods demand more bankcard credit, perhaps because of legal issues that make it difficult to borrow against real estate on many reservations. Then, β^S in expression (2) must be negative. In this case, a statistically significant negative estimate of our reduced-form coefficient on the neighborhood racial composition variable is indeed consistent with lenders' discrimination based on neighborhood racial characteristics.

Suppose, instead, that β^D in expression (1) is negative: all else equal, Indian country residents from predominantly American Indian neighborhoods demand less bankcard credit than Indian country residents from white neighborhoods, perhaps due to specific culturally transmitted preferences or historically determined mistrust in financial institutions among American Indians. It then follows that β^S in expression (2) *could* be negative. But it could also be equal to zero, or even positive (although not too large in magnitude), in which case lenders actually extend more credit to the Indian Country residents who reside in predominantly American Indian neighborhoods that to the Indian Country residents who reside in neighborhoods with a low share of American Indians. Since we do not have any special insight into, or evidence on, which of the competing assumptions—$\beta^D\geq0$ or $\beta^D<0$—is more appropriate, we strongly urge against interpreting our reduced-form results as conclusive evidence of lenders' discrimination based on neighborhood characteristics in Indian Country.

On the other hand, we contend that our estimates of coefficients on the variables capturing individual's credit history are better indicative of the effect of these variables on credit supply. To see this, consider the following argument concerning an individual's Equifax Risk Score (analogous argument applies to an individual's history of bankruptcy). While an individual's Equifax Risk Score undoubtedly affects credit supply, it less likely affects credit demand. That is, indicator variables capturing an individual's Equifax Risk Score decile are elements of vector $\mathbf{x}^S$ in expression (2), but do not appear in expression (1). With a^D<0 (see above), based on expression (4e), the sign of our reduced-form estimates of the coefficients on a given Equifax Risk Score decile indicator variable therefore coincides with the sign of the corresponding structural supply coefficient. Furthermore, since $|a^D|$<1, it follows that our reduced-form estimates of the coefficients on credit history variables quite plausibly underestimate the (absolute) magnitude of the relevant structural supply parameters.

In sum, to the extent that the wide range of our controls and fixed effects mitigates the omitted variable bias, our reduced form estimates may be interpreted as evidence that an individual's credit history, as captured by the Equifax Risk Score and incidence of personal bankruptcy, is a quantitatively important supply-side determinant of bankcard credit limits in Indian Country. In contrast, our results are ultimately inconclusive about the presence (or absence) of lenders' discrimination based on neighborhood racial characteristics. To probe this issue further, we turn to additional empirical tests.

4. Further Empirical Investigations: Effects on Credit Access and Delinquency

4.1. Outcome Variables and Empirical Approach

Given the challenges, noted in Section 3, with the interpretation of results based on measures of credit limit as the outcome variable, in this section we extend our analysis of the role of neighborhood characteristics and individual's credit history by examining two additional bankcard credit outcomes of interest: credit access and delinquency. In areas where credit is overall scarce, as is in general true in the case of Indian Country (see Dimitrova-Grajzl et al. 2015), access to bankcard credit, as measured by whether an individual has any bankcards at all, may be a more important outcome than the actual amount of credit granted.

Similarly, an understanding of whether delinquency rates vary across neighborhoods with different racial composition may help shed light on the presence of credit suppliers' discrimination by neighborhood racial characteristics. One commonly made argument (see, e.g., Becker 1957) suggests that lenders who dislike lending to minorities choose to extend credit to minority dominated neighborhoods only in exchange for a higher return on their investment. The required higher return could be obtained by setting a higher credit quality threshold for borrowers in minority neighborhoods, leading to *lower* default rates in minority dominated neighborhoods.[22] However, the higher return could also be obtained by varying contractual conditions such as credit limits and repayment terms. *For a given awarded total credit limit*, the presence of racial neighborhood-based discrimination by lenders may therefore also be fully consistent with *higher* borrower default rates if residents of minority neighborhoods are subject to elevated interest rates on repayment of debt or higher fees (so-called *reverse redlining*).[23]

To define our measure of bankcard access, we use the sample of individuals currently without a bankcard and further condition our sample on those individuals whose credit history indicates a recent credit inquiry (see Table A2). By conditioning our sample on individuals with a recent 'hard' credit inquiry (an inquiry made by a lending institution that typically follows a consumer's loan application), our reduced-form estimates more plausibly reflect credit supply

[22] See Han (2004: 6; 2011: 5) for references to the literature that uses default probability as the outcome of interest to study discrimination.
[23] See Han (2004) for a formal argument suggesting that discrimination in lending is consistent with higher (as opposed to lower) delinquency rates.

rather than credit demand effects. Our measure of bankcard credit access is an indicator variable equal to one if an individual receives a bankcard in the next quarter (*Will Get First Card*).

Our measure of delinquency is an indicator variable equal to one if the individual has at least one bankcard for which the balance is 90 days or more past due at some point in the next 24 months (*90 Days Past Due*). The 90 days and 24 months cut-offs corresponds to the industry standard for defining delinquency.[24]

When examining the determinants of both *Will Get First Credit* and *90 Days Past Due* outcome variables, we rely on a linear probability model for reasons of computational tractability and ease of interpretation of marginal effects. To address the inherent violation of the homoscedasticity assumption under the linear probability model, we base inference on heteroskedasticity-corrected standard errors and follow the clustering approach outlined in Section 3.2. The choice of explanatory variables and various fixed effects that we use likewise follows the basic strategy outlined in Section 3.2. In the specifications with *90 Days Past Due* as the outcome variable, we further include individual's total bankcard credit limit (see Table A2) to take into account that, as argued above, the likelihood of delinquency crucially depends on the credit limit awarded to an individual.

We include either county-by-quarter or block group-by-quarter fixed effects. When we use county-by-quarter fixed effects, we also include the indicator variables for whether an individual resides on a reservation or in an area adjacent to a reservation. In a subset of specifications with county-by-quarter effects we further include the full range of time-invariant socio-economic controls from the 2000 Census, measured at the block group level (see Table A1).

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[24] The Equifax Risk Score we use, for example, is "designed to help predict the likelihood of a consumer becoming 90+ days delinquent within 24 months" (http://www.equifax.com/business/equifax-risk-score).

4.2. Results: Credit Access

The credit access results for the outcome variable *Will Get First Card* are presented in Table 6. The coefficient on the neighborhood racial composition variable is negative and statistically significant across all three specifications. The magnitude of the implied negative effect on the likelihood of obtaining a first bankcard in the next quarter if residing in a fully American Indian neighborhood as opposed to a neighborhood with no American Indians is halved when we control for Census block group-level socio-economic controls in addition to county-by-quarter effects (see column (2) versus column (1) of Table 6). Unlike in the case of the *First Credit Limit* regressions (see Section 3.2.1 and Table 4), the effect of neighborhood racial composition remains statistically significant even when we replace county-by-quarter effects and Census block group-level socio-economic controls with block group-by-quarter effect. Based on the estimates in column (3) of Table 6, in comparison with consumers who reside in neighborhoods without American Indians, consumers who reside in neighborhoods where all residents are American Indian and are currently without any bankcards are on average about 1.7 percentage points less likely to receive a bankcard in the next quarter. With the mean likelihood for the sample that the consumer will obtain a card in the next quarter if they do not currently possess one equal to 7.5 percent (see Table 3), the effect of neighborhood racial composition on bankcard access is also economically significant.

We find no statistically significant effect of the neighborhood's location vis-à-vis a reservation (see columns (1) and (2)). This result holds even if we omit controlling for racial neighborhood composition and replace county-by-quarter effects with state-by-year effects (not reported). Reservation border per se does not matter for bankcard credit access.

In contrast, an individual's credit history matters significantly. The effect of the Equifax Risk Score is monotonic. Based on the estimates in column (3), relative to possessing Equifax Risk

Score in the lowest (first) decile of the distribution, possessing Equifax Risk Score in the fifth decile of the distribution is all else equal associated with a 2.2 percent, and possessing Equifax Risk Score in the highest (tenth) decile with 4.2 percent, increase in the prospects of obtaining a bankcard in the following quarter. Individual's recent history of bankruptcy is likewise an important determinant of credit access. In particular, having recently filed for bankruptcy is ceteris paribus associated with a *higher* likelihood of obtaining a bankcard in the following quarter, a result that suggests that lenders, especially those specializing in the high-risk segment of the market, are willing to extend credit to recently bankrupt consumers. Furthermore, the type of bankruptcy filing matters. The magnitude and statistical significance of the Chapter 13 bankruptcy effect monotonically increases with time since the individual filed for bankruptcy. In contrast, the magnitude and statistical significance of Chapter 7 bankruptcy effect decreases with time since bankruptcy filing.

The documented differential effect of Chapter 7 versus Chapter 13 bankruptcy on bankcard credit access may be explained by the substantive legal differences between the two bankruptcy options. The law prevents a consumer with a recent Chapter 7 bankruptcy filing to file for another Chapter 7 bankruptcy in the next seven years since the first filing. In contrast, a Chapter 13 bankruptcy filing can be converted to a Chapter 7 filing. As a consequence, consistent with our findings, consumers who recently filed for Chapter 7 bankruptcy are relatively more attractive to bankcard issuers targeting the riskiest segment of the consumer market than the consumers that recently filed for Chapter 13 bankruptcy.

4.3. Results: Delinquency

The delinquency results for the outcome variable *90 Days Past Due* are shown in Table 7. The coefficient on the neighborhood racial composition variable is positive and statistically significant across all three specifications in Table 7. The magnitude of the implied positive effect on the likelihood of delinquency over the next 24 months of residing in a fully American Indian neighborhood relative to residing in a neighborhood with no American Indians decreases by more than a third when we control for Census block group-level socio-economic controls in addition to county-by-quarter effects (see column (2) versus column (1) of Table 7). Replacing county-by-quarter effects and Census block group-level socio-economic controls with block group-by-quarter effects further decreases the magnitude of the coefficient. Based on the estimates in column (3), in comparison with consumers who reside in neighborhoods without any American Indian residents, consumers who reside in neighborhoods where all residents are American Indian are on average about 1.6 percentage points more likely to have at least one bankcard for which the balance is 90 days or more past due at some point in the next 24 months. Given that the mean likelihood of delinquency in the sample equals 11.6 percent (see Table 3), the effect of neighborhood racial composition is non-trivial in magnitude.

We find no statistically significant effect of the neighborhood's location vis-à-vis a reservation per se (see columns (1) and (2)), a result that again holds even if we omit controlling for neighborhood's racial composition and replace county-by-quarter effects with state-by-quarter effects (not reported). The effect of an individual's credit history on the likelihood of delinquency, however, is statistically highly significant and large in magnitude. According to the estimates in column (3), relative to possessing Equifax Risk Score in the lowest (first) decile of the distribution, possessing Equifax Risk Score in the fifth decile of the distribution is all else equal associated with a 34 percent, and possessing Equifax Risk Score in the highest (tenth) decile with a nearly 44 percent, decrease in the likelihood that an individual will have at least one bankcard for which the balance is 90 days or more past due at some point in the next 24 months. The effect of having filed for either Chapter 7 or Chapter 13 bankruptcy some time during the past six years is statistically significant and negative, a result suggesting that recent bankruptcy experience may, at least in the short run, disciplines consumers to better manage their credit. In addition, the reduced debt burden immediately following bankruptcy likely helps the consumer remain current. The disciplining effect of bankruptcy, however, is less clear if we consider a longer-run effect. Based on the results in column (3), having filed for Chapter 13 bankruptcy seven to nine years ago increases the consumer's delinquency prospects, a finding indicative of a pattern of repeated delinquency among the delinquent consumers.

4.4. Discussion

Our reduced-form results on credit access resonate with the results on the total awarded credit limit from Section 3.2. Conditional on not possessing any bankcards, residing in a neighborhood with more American Indian residents is all else equal associated with a lower likelihood of obtaining a bankcard in the next quarter. The implied effect is non-trivial in magnitude. These results are consistent with the possibility of lenders' discrimination based on racial neighborhood characteristics. However, the already noted challenges associated with the interpretation of reduced-form results as supply parameters do not readily facilitate interpretation of four findings as conclusive evidence in favor of lenders' discrimination.

The delinquency regression results are not consistent with the argument that in the presence of lenders' discrimination based on neighborhood racial characteristics the delinquency rates should be lower in minority dominated neighborhoods because discriminatory lenders are only willing to extent credit to minority neighborhoods in exchange for a higher expected return (see, e.g., Becker 1957). Instead, our results resonate with the line of reasoning suggesting that in the presence of lenders' discrimination based on neighborhood racial characteristics, delinquency rates should be higher in minority neighborhoods (see, e.g., Hahn 2004). To further investigate this finding, we also estimated a specification where we interacted our neighborhood racial composition variable (*Percent American Indian*) variable with a full set of indicator variables for the decile of an individual's Equifax Risk Score. If lenders discriminate based on neighborhood racial characteristics and, therefore, for given awarded credit limits delinquency rates should on average be higher in minority neighborhoods, we would expect that, for given awarded credit limits, the delinquency rates in minority neighborhoods will be comparatively higher among consumers with low Equifax Risk Scores, who in general have fewer and in contractual terms worse credit offers to choose among than the consumers with high Equifax Risk Scores. The results (not reported) are consistent with this hypothesis: the effect of *Percent American Indian* on delinquency is positive and statistically significant conditional on individual possessing Equifax Risk Score in the seventh or lower decile and negative and statistically insignificant conditional on individual possessing Equifax Risk Score in the top three deciles of the Equifax Risk Score distribution.

The lack of information on the contractual details of the bankcard credit (such as fees and terms of debt repayment) in our data is a potential source of omitted variable bias, which may in turn drive the observed positive association between neighborhood racial composition and delinquency. Hence, as in the case of our findings for other outcome variables, our results on delinquency should not be viewed as hard evidence in favor of bankcard issuers' discrimination.

Finally, while the estimated reduced-form effects of neighborhood racial composition on credit access and delinquency are small in magnitude, the effects of an individual's credit history as captured by the Equifax Risk Score and recent bankruptcy are notably larger. These results point to the importance of individual's credit history as a predictor of credit access and delinquency in American Indian neighborhoods.

5. Conclusion

We examine whether persistent concerns about lenders' discrimination based on neighborhood racial characteristics and the resulting lack of access to, and usage of, bankcard credit in minority communities in the United States can be empirically substantiated in the thus far unexplored context of Indian Country. Using data on individual credit histories available in the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) and Census data on neighborhood characteristics, we find that residing in a neighborhood on or near an American Indian reservation with a large share of American Indian residents is all else equal associated with lower total bankcard credit limit, lower likelihood of obtaining a bankcard, and higher delinquency than residing in a neighborhood on or near an American Indian reservation with a smaller share of American Indian residents. In contrast, the location of an individual's neighborhood vis-à-vis a reservation exhibits no effect on bankcard credit outcomes.

Our findings are therefore *consistent with* the possibility that lenders in Indian Country indeed discriminate based on neighborhood racial composition. Yet due to data constraints and limitations of the reduced-form regression approach, our results should *not* be readily interpreted as conclusive evidence thereof. To shed further light on this important policy question in the absence of a true experimental setting, future research will need to draw on even more detailed data. In particular, information about individual income and contractual terms of the credit relationship such as the interest rate, fees, and other terms of debt repayment would together with bankcard credit demand-specific variables facilitate a cleaner identification of structural bankcard credit supply parameters.

Our empirical results imply that individual's Equifax Risk Score and recent history of bankruptcy are robust predictors of bankcard credit outcomes. Indeed, consumers who raise their scores even by relatively moderate amounts can be expected to improve their access to bankcard credit, increase awarded credit limit, and decrease delinquency prospects by a significantly larger extent than predicted by the move from an Indian Country neighborhood with a high share of American Indian residents to an Indian Country neighborhood with a low share of American Indian residents. This suggests that financial education and credit counseling (see, e.g., Brown et al. 2014)—services often provided by community development financial institutions and other community service organizations in tribal communities—are important for improving bankcard credit access and usage on and near reservations.

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Table 1: Variable Description for Outcome Variables and Key Explanatory Variables

Panel A: Outcome Variables			
Variable	Description	Unit of observation	Source
First Credit Limit	Logged next quarter's total credit limit on all bankcard for individuals currently without a bankcard.	Individual	CCP
Next Credit Limit	Logged next quarter's total credit limit summed across all bankcard accounts.	Individual	CCP
Will Get First Card	Indicator variable equal to 1 if the individual gets one or more new bankcards in the following year, and 0 otherwise.	Individual	CCP
90 Days Past Due	Indicator variable equal to 1 if the individual has at least one bankcard for which the balance is at least 90 days past due at some point in the next 24 months, and 0 otherwise.	Individual	CCP
Panel B: Key Explanatory Variables			
Variable	Description	Unit of observation	Source
Share American Indian	Percent of population (aged 18 or over) that identifies as American Indian either as single race or in part.	Census block	Census 2000, Summary File 1, Table P5
On Reservation	Indicator variable equal to 1 if the Census block where the individual resides lies within the boundaries of a reservation, and 0 otherwise.	Census block	Census 2000, TIGER
Adjacent to Reservation	An indicator variable equal to 1 if the Census block where an individual resides lies adjacent to a reservation border and not within any reservation, and 0 otherwise.	Census block	Census 2000, TIGER
ERS X^{th} Decile	Indicator variable equal to 1 if the individual's Equifax Risk Score (ERS) falls in the X^{th} decile of the distribution based on the full sample.	Individual	CCP
Ch. 7 Bankruptcy Last X-Y Yrs	Indicator variable equal to 1 if the individual filed for Chapter 7 bankruptcy that resulted in a discharge between X and Y years ago, and 0 otherwise.	Individual	CCP
Ch. 13 Bankruptcy Last X-Y Yrs	Indicator variable equal to 1 if the earliest indication of Chapter 13 bankruptcy activity (filing, dismissal or discharge) occurred between X and Y years ago, and 0 otherwise.	Individual	CCP

Notes: CCP stands for the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 2: Descriptive Statistics for Key Explanatory Variables

Panel A: First Credit Limit sample (see Table 4)					
Explanatory Variable	No. Obs.	Mean	Std. Dev.	Min.	Max.
Census block level					
Share American Indian	232,613	0.0343	0.1100	0	1
On Reservation	232,613	0.0301	0.1709	0	1
Adjacent to Reservation	232,613	0.0126	0.1117	0	1
Individual level					
Equifax Risk Score (ERS)	232,613	637.9	90.8	303	841
Ch. 7 Bankruptcy Last 0-3 Yrs	232,613	0.0476	0.2130	0	1
Ch. 7 Bankruptcy Last 4-6 Yrs	232,613	0.0334	0.1798	0	1
Ch. 7 Bankruptcy Last 7-9 Yrs	232,613	0.0171	0.1296	0	1
Ch. 13 Bankruptcy Last 0-3 Yrs	232,613	0.0112	0.1051	0	1
Ch. 13 Bankruptcy Last 4-6 Yrs	232,613	0.0125	0.1110	0	1
Ch. 13 Bankruptcy Last 7-9 Yrs	232,613	0.0059	0.0763	0	1
Age	232,613	38.75	13.45	18	70
Panel B: (*90 Days Past Due* sample (see Table 7)					
Explanatory Variables	No. Obs.	Mean	Std. Dev.	Min.	Max.
Census block level					
Share American Indian	9,081,740	0.0244	0.0786	0	1
On Reservation	9,081,740	0.0223	0.1475	0	1
Adjacent to Reservation	9,081,740	0.0127	0.1119	0	1
Individual level					
Equifax Risk Score (ERS)	9,081,740	689.4	106.6	282	848
Ch. 7 Bankruptcy Last 0-3 Yrs	9,081,740	0.0231	0.1501	0	1
Ch. 7 Bankruptcy Last 4-6 Yrs	9,081,740	0.0320	0.1760	0	1
Ch. 7 Bankruptcy Last 7-9 Yrs	9,081,740	0.0191	0.1367	0	1
Ch. 13 Bankruptcy Last 0-3 Yrs	9,081,740	0.0046	0.0675	0	1
Ch. 13 Bankruptcy Last 4-6 Yrs	9,081,740	0.0071	0.0840	0	1
Ch. 13 Bankruptcy Last 7-9 Yrs	9,081,740	0.0044	0.0662	0	1
Age	9,081,740	44.63	12.73	18	68

Notes: Equifax Risk Score is the raw Equifax's proprietary credit risk score indicating default risk; it ranges from 280 and 850 with lower scores correspond to higher estimated risk of default. Age is consumer's age in years. Computed using data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 3: Descriptive Statistics for Outcome Variables

Outcome Variable	No. Obs.	Mean	Std. Dev.	Min.	Max.
First Credit Limit	232,613	7.1006	1.4777	0	14.2775
Next Credit Limit	10,910,693	9.0701	1.5721	0	16.1181
Will Get First Card	2,022,305	0.0747	0.2629	0	1
90 Days Past Due	9,081,740	0.1163	0.3206	0	1

Notes: Computed using data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 4: Regression Results, *First Credit Limit*

Explanatory Variables	(1)	(2)	(3)
Census block level			
Share American Indian	-0.2468***	-0.1138***	-0.1043
	(0.0394)	(0.0394)	(0.122)
On Reservation	0.0263	0.0072	
	(0.0236)	(0.0238)	
Adjacent to Reservation	0.0113	0.0017	
	(0.0235)	(0.0235)	
Individual level			
ERS 2nd Decile	-0.0634***	-0.0667***	-0.0679***
	(0.00954)	(0.00970)	(0.0220)
ERS 3rd Decile	0.0308***	0.0201*	0.0247
	(0.0115)	(0.0117)	(0.0231)
ERS 4th Decile	0.4293***	0.4118***	0.4199***
	(0.0131)	(0.0133)	(0.0247)
ERS 5th Decile	0.9336***	0.9048***	0.9343***
	(0.0132)	(0.0134)	(0.0259)
ERS 6th Decile	1.3889***	1.3507***	1.3977***
	(0.0137)	(0.0138)	(0.0274)
ERS 7th Decile	1.8370***	1.7898***	1.7983***
	(0.0140)	(0.0142)	(0.0305)
ERS 8th Decile	2.1079***	2.0466***	2.0524***
	(0.0163)	(0.0163)	(0.0324)
ERS 9th Decile	2.2143***	2.1393***	2.1529***
	(0.0178)	(0.0178)	(0.0368)
ERS 10th Decile	2.349***	2.2530***	2.2788***
	(0.0196)	(0.0195)	(0.0430)
Ch. 7 Bankruptcy Last 0-3 Yrs	-0.2538***	-0.2674***	-0.2562***
	(0.0159)	(0.0159)	(0.0307)
Ch. 7 Bankruptcy Last 4-6 Yrs	-0.1754***	-0.1836***	-0.1890***
	(0.0149)	(0.0149)	(0.0364)
Ch. 7 Bankruptcy Last 7-9 Yrs	-0.0286*	-0.0387***	-0.0091
	(0.0176)	(0.0177)	(0.0464)
Ch. 13 Bankruptcy Last 0-3 Yrs	-0.1644***	-0.1812***	-0.1801***
	(0.0284)	(0.0282)	(0.0603)
Ch. 13 Bankruptcy Last 4-6 Yrs	-0.2449***	-0.2538***	-0.2085***
	(0216)	(0.0216)	(0.0555)
Ch. 13 Bankruptcy Last 7-9 Yrs	-0.1299***	-0.1358***	-0.0717
	(0.0273)	(0.0274)	(0.0739)
Age Fixed Effect	Yes	Yes	Yes
Census block group level			
Socio-Economic Controls	No	Yes	No
Fixed Effects	County by Quarter	County by Quarter	Block Group by Quarter
R-squared	0.394	0.397	0.762
No. Obs.	232,613	232,613	232,613

Notes: The table presents results based on OLS regressions for First Credit Limit as the outcome variable. Reported standard errors are heteroscedasticity-robust and clustered (see text for details). *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. Computed using data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 5: Regression Results, *Next Credit Limit*

Explanatory Variables	(1)	(2)
Census block level		
Share American Indian	-0.0554***	-0.0385*
	(0.0208)	(0.0211)
On Reservation	0.0194*	0.0180
	(0.0114)	(0.0115)
Adjacent to Reservation	0.0110	0.0081
	(0.0104)	(0.0104)
Individual level		
ERS 2nd Decile	-0.1515***	-0.1514***
	(0.0018)	(0.0020)
ERS 3rd Decile	-0.1739***	-0.1738***
	(0.0023)	(0.0023)
ERS 4th Decile	-0.1194***	-0.1195***
	(0.0027)	(0.0027)
ERS 5th Decile	-0.0280***	-0.0282***
	(0.0030)	(0.0030)
ERS 6th Decile	0.0694***	0.0690***
	(0.0032)	(0.0032)
ERS 7th Decile	0.1228***	0.1224***
	(0.0034)	(0.0034)
ERS 8th Decile	0.1298***	0.1293***
	(0.0036)	(0.0036)
ERS 9th Decile	0.1363***	0.1357***
	(0.0037)	(0.0037)
ERS 10th Decile	0.1483***	0.1478***
	(0.0039)	(0.0039)
Ch. 7 Bankruptcy Last 0-3 Yrs	-1.3558***	-1.3558***
	(0.0129)	(0.0129)
Ch. 7 Bankruptcy Last 4-6 Yrs	-1.0612***	-1.0615***
	(0.0137)	(0.0138)
Ch. 7 Bankruptcy Last 7-9 Yrs	-.8582***	-0.8585***
	(0.0150)	(0.0150)
Ch. 13 Bankruptcy Last 0-3 Yrs	-1.2659***	-1.2655***
	(0.0277)	(0.0277)
Ch. 13 Bankruptcy Last 4-6 Yrs	-1.0500***	-1.0492***
	(0.0303)	(0.0302)
Ch. 13 Bankruptcy Last 7-9 Yrs	-0.7580***	-0.7576***
	(0.0331)	(0.0331)
Age Fixed Effect	Yes	Yes
Census block group level		
Socio-Economic Controls	No	Yes
Individual FE	Yes	Yes
Year FE	Yes	Yes
Quarter FE	Yes	Yes
R-squared	0.885	0.885
No. Obs.	10,910,693	10,910,693

Notes: The table presents results based on OLS regressions for Next Credit Limit as the outcome variable. Reported standard errors are heteroscedasticity-robust and clustered (see text for details). *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. Computed using data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 6: Regression Results, *Will Get First Card*

Explanatory Variables	(1)	(2)	(3)
Census block level			
Share American Indian	-0.0154***	-0.0076***	-0.0174***
	(0.0023)	(0.0023)	(0.0037)
On Reservation	0.0016	0.0018	
	(0.0017)	(0.0017)	
Adjacent to Reservation	0.0025	0.0025	
	(0.0017)	(0.0017)	
Individual level			
ERS 2nd Decile	-0.0016**	-0.0017**	-0.0018***
	(0.0007)	(0.0007)	(0.0007)
ERS 3rd Decile	0.0055***	0.0050***	0.0046***
	(0.0009)	(0.0009)	(0.0007)
ERS 4th Decile	0.0177***	0.0166***	0.0162***
	(0.0011)	(0.0011)	(0.0008)
ERS 5th Decile	0.0247***	0.0231***	0.0223***
	(0.0013)	(0.0013)	(0.0009)
ERS 6th Decile	0.0346***	0.0323***	0.0318***
	(0.0015)	(0.0015)	(0.0011)
ERS 7th Decile	0.0354***	0.0323***	0.0307***
	(0.0017)	(0.0017)	(0.0012)
ERS 8th Decile	0.0402***	0.0363***	0.0347***
	(0.0019)	(0.0019)	(0.0015)
ERS 9th Decile	0.0463***	0.0418***	0.0401***
	(0.0022)	(0.0022)	(0.0019)
ERS 10th Decile	0.0497***	0.0445***	0.0422***
	(0.0030)	(0.0030)	(0.0028)
Ch. 7 Bankruptcy Last 0-3 Yrs	0.0383***	0.0369***	0.0365***
	(0.0012)	(0.0012)	(0.0012)
Ch. 7 Bankruptcy Last 4-6 Yrs	0.0167***	0.0156***	0.0154***
	(0.0012)	(0.0011)	(0.0013)
Ch. 7 Bankruptcy Last 7-9 Yrs	0.0173***	0.0162***	0.0169***
	(0.0016)	(0.0016)	(0.0018)
Ch. 13 Bankruptcy Last 0-3 Yrs	0.0026*	0.0009	0.0006
	(0.0016)	(0.0016)	(0.0018)
Ch. 13 Bankruptcy Last 4-6 Yrs	0.0065***	0.0054***	0.0049***
	(0.0016)	(0.0016)	(0.0018)
Ch. 13 Bankruptcy Last 7-9 Yrs	0.0112***	0.0103***	0.0097***
	(0.0024)	(0.0023)	(0.0027)
Age Fixed Effect	Yes	Yes	Yes
Census block group level			
Socio-Economic Controls	No	Yes	No
Fixed Effects	County by Quarter	County by Quarter	Block Group by Quarter
R-squared	0.013	0.014	0.168
No. Obs.	2,022,305	2,022,305	2,022,305

Notes: The table presents results based on OLS regressions for Will Get First Card as the outcome variable. Reported standard errors are heteroscedasticity-robust and clustered (see text for details). *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. Computed using data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 7: Regressions Results, *90 Days Past Due*

Explanatory Variables	(1)	(2)	(3)
Census block level			
Share American Indian	0.0325***	0.0206***	0.0157***
	(0.0021)	(0.0020)	(0.0025)
On Reservation	0.0001	0.0002	
	(0.0009)	(0.0010)	
Adjacent Reservation	-0.0005	-0.0010	
	(0.0008)	(0.0008)	
Individual level			
ERS 2nd Decile	-0.1242***	-0.1240***	-0.1239***
	(0.0010)	(0.0010)	(0.0008)
ERS 3rd Decile	-0.1913***	-0.1907***	-0.1906***
	(0.0011)	(0.0011)	(0.0008)
ERS 4th Decile	-0.2762***	-0.2750***	-0.2750***
	(0.0012)	(0.0012)	(0.0007)
ERS 5th Decile	-0.3465***	-0.3450***	-0.3442***
	(0.0012)	(0.0012)	(0.0007)
ERS 6th Decile	-0.3916***	-0.3896***	-0.3889***
	(0.0014)	(0.0014)	(0.0006)
ERS 7th Decile	-0.4163***	-0.4140***	-0.4132***
	(0.0017)	(0.0016)	(0.0006)
ERS 8th Decile	-0.4299***	-0.4273***	-0.4263***
	(0.0018)	(0.0018)	(0.0006)
ERS 9th Decile	-0.4373***	-0.4343***	-0.4332***
	(0.0019)	(0.0019)	(0.0006)
ERS 10th Decile	-0.4427***	-0.4391***	-0.4379***
	(0.0020)	(0.00194)	(0.0006)
Ch. 7 Bankruptcy Last 0-3 Yrs	-0.0404***	-.0398***	-0.0393***
	(0.0011)	(0.0011)	(0.0008)
Ch. 7 Bankruptcy Last 4-6 Yrs	-0.0190***	-0.0187***	-0.0180***
	(0.0008)	(0.0008)	(0.0007)
Ch. 7 Bankruptcy Last 7-9 Yrs	0.0008	0.0010	0.0006
	(0.0013)	0.0014	(0.0009)
Ch. 13 Bankruptcy Last 0-3 Yrs	-0.0664***	-0.0656***	-0.0651***
	(0.0024)	(0.0024)	(0.0021)
Ch. 13 Bankruptcy Last 4-6 Yrs	-0.0105***	-0.0101***	-0.0089***
	(0.0017)	(0.0017)	(0.0016)
Ch. 13 Bankruptcy Last 7-9 Yrs	0.0183	0.0186***	0.0175***
	(0.0022)	(0.0022)	(0.0021)
Age Fixed Effect	Yes	Yes	Yes
Census block group level			
Socio-Economic Controls	No	Yes	No
Fixed Effects	County by Quarter	County by Quarter	Block Group by Quarter
R-squared	0.198	0.198	0.198
No. Obs.	9,081,740	9,081,740	9,081,740

Notes: The table presents results based on OLS regressions for 90 Days Past Due as the outcome variable. Reported standard errors are heteroscedasticity-robust and clustered (see text for details). *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. Computed using data from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table A1: Census Block Group Level Socio-Economic Controls

Variable	Description	Source
Percent Foreign	Percent of population born in a foreign country	Census 2000, Summary File 3, Table P21
inc010	Percent of households with income between $10,000 and $15,000.	Census 2000, Summary File 3, Table P52
inc015 ... inc150	Defined analogously to inc010 with number in variable name representing the lower bound of the bracket.	Census 2000, Summary File 3, Table P52
inc200	Percent of households with income of at least $200,000.	Census 2000, Summary File 3, Table 52
Percent Male HS	Percent of male population (aged 25+) with a high school diploma or equivalent and no formal higher education.	Census 2000, Summary File 3, Table P37
Percent Male Gt HS	Percent of male population (aged 25+) with at least some college education	Census 2000, Summary File 3, Table P37
Percent Female HS	Percent of female population (aged 25+) with a high school diploma or equivalent and no formal higher education.	Census 2000, Summary File 3, Table P37
Percent Female Gt HS	Percent of female population (aged 25+) with at least some college education	Census 2000, Summary File 3, Table P37
Percent Male Married	Percent of male population (aged 15+) who are married	Census 2000, Summary File 3, Table P18
Percent Male Widowed	Percent of male population (aged 15+) who are widowed	Census 2000, Summary File 3, Table P18
Percent Male Divorced	Percent of male population (aged 15+) who are divorced	Census 2000, Summary File 3, Table P18
Percent Female Married	Percent of female population (aged 15+) who are married	Census 2000, Summary File 3, Table P18
Percent Female Widowed	Percent of female population (aged 15+) who are widowed	Census 2000, Summary File 3, Table P18
Percent Female Divorced	Percent of female population (aged 15+) who are divorced	Census 2000, Summary File 3, Table P18
Employment - Population Ratio	Percent of population (aged 16+) that is employed	Census 2000, Summary File 3, Table P43
Percent Vacant	Percent of housing units that are vacant	Census 2000, Summary File 3, Table H6
Percent Owner Occupied	Percent of occupied housing units that are owned by the occupant.	Census 2000, Summary File 3, Table H7
Percent Mortgage	Percent of owner-occupied housing units with a mortgage, contract to purchase or similar debt.	Census 2000, Summary File 3, Table H80
Log Housing Unit Median Rent	Log of the median rent among renter-occupied housing units.	Census 2000, Summary File 3, Table H63
Log Housing Unit Median Value	Log of the median value of owner-occupied housing units.	Census 2000, Summary File 3, Table H76
Percent Public Assistance	Percent of households with public assistance income.	Census 2000, Summary File 3, Table P64

Table A2: Other Individual-Level Explanatory and Screening Variables

Variable	Description	Regression	Source
Time Since Last Credit Change	Time since the last change in the credit limit.	Next Credit Limit	CCP
Sign of Last Credit Change	Sign of the last change in the credit limit.	Next Credit Limit	CCP
Bankcard Credit	Total credit limit summed across all bankcards in the current quarter.	90 Days Past Due	CCP
Inquiry	Indicator variable equal to 1 if there is a hard-pull inquiry in the next, current or last quarter, and 0 otherwise.	Will Get First Card	CCP

Notes: CCP stands for the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.