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Credit Card Redlining

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Abstract

This paper evaluates the presence of racial disparities in the issuance of consumer credit. Using a unique and proprietary database of credit histories from a major credit bureau, this paper links location-based information on race with individual credit files. After controlling for the influence of such other place-specific factors as crime, housing vacancy rates, and general population demographics, the paper finds qualitatively large differences in the amount of credit offered to similarly qualified applicants living in Black versus White areas. An instrumental variables approach allows the paper to distinguish between issuer-provided credit (supply) and utilization of credit (demand), where instruments for demand are derived from social theory à la Veblen (i.e., 'keeping up with the Joneses'). The results suggest that the observed differences in credit lines by racial composition of neighborhood are largely driven by issuer decisions rather than by demand.

JEL codes: J15, G21

Keywords: Credit cards, racial disparities, access to credit, keeping up with the Joneses, African American, redlining

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1 Introduction

This paper evaluates the presence of racial disparities in the supply of revolving consumer credit. Disparities in access to such consumer credit as credit cards are critical to assess because this form of credit is generally the first form of credit accessed by consumers. In order to qualify for a mortgage, one typically has to "build" a credit history. This marks a significant change that has taken place over the past few decades. In the 1960s, borrowing was predominantly related to home purchases. However, households now have more access to personal loans, auto loans, educational loans, and, significantly, credit cards; building credit involves using one or more of these products to incur debt and successfully repay it. As a result, disparities in access at this stage will be magnified when consumers seek access to such products as mortgages.

To frame the research for this paper, it is useful to consider a couple of borrowers. Consider two individuals, each of whom is the same age and earns a similar salary. Our two individuals have similar credit histories in the sense that they have both obtained and used credit with similar patterns of delinquency and repayment. Thus, the two have identical credit scores. The only characteristic that will distinguish our borrowers is the racial composition of the neighborhood in which they live. Individual A lives in a predominantly White neighborhood and individual B lives in a majority Black one.[1]

This paper's principal observation is that remarkably, in spite of identical scores and identical community characteristics, our individual in the Black neighborhood receives less consumer credit (e.g. fewer scredit cards) than the individual in the White area. That is, in spite of the fact that both have been assessed to have similar risks of nonpayment, as determined by the credit score, the person living in the Black area has less ability to access credit. Notice here that the example does not identify the race of the individuals, only the neighborhoods in which they live.

As is well known, there are large correlations between racial compositions and other socioeconomic factors that may be related to an individual's ability to repay debt. For example, high vacancy rates may impact home equity appreciation rates, and thus in areas with low growth, individuals may not be able to subsidize consumer spending with equity financing. Many factors indeed show a correlation between credit quality and neighborhood racial composition. For example, Panel A of Table 1 shows the results of a series of univariate regressions of "months since last delinquency" on a handful of demographic characteristics.[2] Notice that, given the results of this table, the process of an issuer implementing some simple marketing differentiation by such location-based characteristics as crime rates could appear to an outsider as race-based outcome differences even when race is explicitly excluded from consideration.[3] That is, the stylized fact above that individual B received less credit may simply be due to issuers avoiding lending in areas with

[1] This paper uses Black throughout to refer to the self-reported race from the U.S. Census 2000 Summary File.

[2] Li and Rosenblatt (1997) find no relationship between nine census variables and home prices. If one believes that the causal relationship between the use of location-based demographics and credit quality is collateral values, this study is strong evidence of the implausibility of the argument. However, it seems that environmental factors such as neighborhood crime can have an influence on the ability to repay debt without a causal chain that passes through housing collateral values.

[3] The legal term for the appearance of outcome differences is "disparate impact." This paper goes to great length to avoid taking a legal stand on this topic; in fact, it is not clear from existing legal precendent how the results of this paper should be treated. Some discussion is available below.

endemic crime, vacancy, etc. That is, an issuer could argue that using race, or one of a number of other factors correlated with race and delinquency, provides information related to profitability: those living in communities with more African Americans appear to have higher default and delinquency rates than those outside. To support this type of argument, panel B of the same table shows a correlation matrix of these variables with the percentage of African Americans in a census block.

This takes us to the second stylized fact: the disparity in credit access persists even after one accounts for the socioeconomic characteristics that one might suspect are correlated with ability repay debt. In fact, it appears to survive the inclusion of numerous demographic and socioeconomic variables available in the census report.

The broad goal of this paper is to distinguish between the two stylized facts above. The first found that there are race-based differences in access at an average level, conditional on credit score. The latter found race-based differences even after conditioning on additional information potentially useful in a credit decision. That is, one wants to know whether race-based differences in credit issuance are present, even after conditioning on non–race-based profitability measures.

To answer the broad question of the presence of a location-based race coefficient, this paper uses a set of data that has not previously been applied to this topic: that is, data from a nationwide representative sample of credit reports. Used in conjunction with publicly available census and crime information, this data gives one a potential window into the methods of issuers. The paper accomplishes this in three ways. One, the data used are new to this literature and provide a number of advantages: (i) the data include individual-level credit reports for a nationally representative and very large sample of individuals; (ii) the reports include information on total credit available and on credit used; and (iii) credit limits provide a logical proxy for supply, while the amount of credit used offers a clear interpretation for demand. This allows one to avoid the simultaneity questions that have confronted some of the mortgage literature. Two, though the quality of the supply proxy is very good and the reduced form may be sufficient for inference, the paper also uses an instrumental variables approach to account for the simultaneous determination of credit limits and utilization. And three, the instruments chosen are based on phenomena related to the correlation of consumer behavior (demand for credit) across individuals in social proximity.

Drawing on these methods, the paper finds evidence of race-based differences in the availability of credit. Though issuers' marketing and underwriting decisions are not fully known, it appears likely that a race variable is included somewhere in the determination of credit availability.

The remainder of this paper is organized as follows. Section 2 provides a review of related methodology and concepts from the mortgage literature. Section 3 discusses the data and section 4 describes the methodology of this paper. The results are presented in section 5, a discussion of potential confounding issues are addressed in section 6, and a conclusion is provided in section 7.

2 Literature Review

The issue of race-based differences in access to credit has received ongoing national attention since it was highlighted decades ago when mortgage disparities were believed to have contributed to urban blight. More recently, Edelberg has found that minorities have systematically worse terms of credit (Edelberg 2007). Following the Second World War, many U.S. cities experienced dramatic disinvestment in urban areas, in part as a consequence of newly forming suburbs. As is well known, these now-poor urban areas are predominantly African American and characterized by low job growth, high crime, and other varieties of social and economic malaise. Among the contributing factors for this poverty was the differential access to credit; specifically, the practice of mortgage "redlining." Broadly speaking, this term refers to a process by which financial institutions avoid mortgage lending in specific geographic areas, typically minority ones. As individuals in these areas were denied loans to buy or build houses, a process of slow deterioration took root. The ensuing conceptual link between credit access and growth has fostered a large literature seeking to evaluate theoretically and empirically the presence of disparities in access to mortgage credit. Ross and Yinger (2002) and Hillier (2002) provide excellent overviews of this line of research.

To date, many empirical studies of supply differentiation have focused on estimating the coefficient of a race variable in a regression of individual mortgage approval decisions. While most studies of these have concentrated on mortgages, the methodological issues faced are instructive for this paper's focus on consumer credit. For example, one specifies:

$$approval_i = \beta_0 + \beta_1 black_i + \beta_2 X_i + \beta_3 percentblack_j + \beta_4 Y_j + \varepsilon_i, \tag{1}$$

where X_i is a vector of such individual characteristics as credit history and income, where i indexes individuals, and Y_j is a set of regional or local characteristics, with j an index of some geographic area. The variables $black_i$ and $percentblack_j$ refer to a variable indicating a Black applicant and a variable measuring the percentage of Black individuals in neighborhood j, respectively. Then, one typically evaluates the significance of the β_1 or β_3 coefficients. Probably the most prominent of these analyses, Munnell et al. (1996), later dubbed the "Boston Fed Study," found a negative coefficient on β_1 that was robust to a myriad of specifications. This paper (as well as Tootell 1996) used individual-level transaction data from the Home Mortgage Disclosure Act (HMDA) along with census tract information and credit histories to show evidence of disparities in access to mortgages.[4] The study finds that, conditional on applying for a mortgage, the probability of receiving credit is lower for Blacks than for Whites.

Though the negative coefficient has often been viewed as evidence of discrimination, it has several other possible interpretations. The first is based on Becker's (1971) argument that some individuals have a "taste" for discrimination. In Becker's formulation, this is costly to the individual and is minimized by competition. The second is the argument that equilibrium phenomena (such as supply differences by group or location) may occur even with ex ante identical groups. Asymmetries can arise based on very minor differences in

[4]Holloway and Wyly (2001) use similar methods, and in a close antecedent to this paper, Duca and Rosenthal (1993) find evidence in the Survey of Consumer Finances of borrowing constraints that are tighter for minorities than for Whites.

preferences (Schelling 1972), based on incentives to specialize (Moro and Norman 2004, Coate and Loury 1993), or based on differences in information precision related to collateral valuation (Lang and Nakamura 1993). One can explain this type of phenomena in the mortgage context as follows: If applicant choices (e.g., whether to apply) are correlated with their own credit quality and with race, then this can lead to correlations in the lender's applicant pool between race and creditworthiness. Applicant actions serve as an informative signal to lenders that can then be used for credit decisions. As a result, one could observe disparities in approval rates across races even if each lending decision is unbiased with respect to race. Notice that this can occur even in the absence of an omitted variables problem.[5] These phenomena reflect the presence of profit-seeking–based statistical lending or marketing criteria that lead, ex-post, to differences in access by race.[6]

In addition to the possibility that the Boston Fed Study's results could be explained by equilibrium disparities arising from sources other than discrimination, Yezer et al. (1994) highlight another potential issue with the study. The authors argue that the loan-to-value ratio (LTV) of a house is simultaneously determined with the accept/reject decision of a lender.[7] Using simulation evidence, they show that their system, which also includes an equation for default, explains how single-equation models can lead to incorrect inference. Though they highlight an important issue with single-equation systems, it appears unlikely to be a problem in the mortgage case: the structure of mortgage loan decisions leads to the ability to ignore the loan-to-value ratio as a simultaneity issue since LTVs are known prior to the time of a credit decision.[8]

Despite the large volume of studies on access to mortgages, little has been researched on other forms of credit.[9] By looking at consumer credit, it's possible to evaluate a potentially unresolved issue in the mortgage literature, namely the determinants of credit quality at the time of a mortgage application. That is, existing mortgage studies take as given the quality of an individual's credit history at the time of the mortgage. If applicants have faced disparities in access to previous forms of credit, the assumption of similar performance conditional on credit history may be inaccurate. Failure to account for prior history would lead to attenuation bias in mortgage studies, strengthening claims of discrimination and calling into question findings of no discrimination. Detailed credit bureau data on individual credit histories allow one to explore the acquisition of credit that can contribute to, or hamper, the ability to obtain a mortgage.

Moreover, the nature of consumer credit allows one to side-step an additional issue in mortgage studies. By their nature, mortgage applications are binary events; agents apply for one (on occasion two or three) or none. Most individual-level studies have used information provided by HMDA, which reveals the loan

[5]The common counter-argument to the signaling case is simply that a similar phenomena could be observed based on an omitted variable. The full argument is articulated in the mortgage case by Longhofer and Peters (2005).

[6]The literature on mortgage lending disparities is very long and a full review is beyond the scope of this paper. Some references on the use of statistical methods to ration supply include Zenou and Boccard (2000), Holloway and Wyly (2001), Ross and Tootell (2004), and Ferguson and Peters (1995). See Ross and Yinger (2002) for a comprehensive review.

[7]The situation suggested by Yezer et al. is that of a borrower with perfect foresight. This enables them to form expectations about the functional form of the lenders' accept/reject decision and essentially make an LTV decision simultaneously with an acceptance probability. Lenders are thus modeled as passive implementers of functional lending criteria.

[8]Phillips-Patrick and Rossi (1996) point out a different endogeneity problem. They note that the credit supply-and-demand functions are simultaneously determined.

[9]There have been studies on redlining in insurance markets. See Squires (1997) for a series of articles on the topic.

approval decision for each application. It has been well acknowledged that this only allows insight into a portion of the possible avenues for disparities in access and does not capture the full supply/demand characteristics of the market. For example, a lender that is potentially willing to issue additional mortgages in an area to individuals of a specific race will not be fully revealed in the database, and individuals who may want a mortgage may thus be discouraged directly or indirectly from applying. Essentially, portions of the supply curve may be unidentified. Though using credit lines as a proxy brings some identification challenges, they provide (nearly) continuous information on credit availability in the form of credit lines.

3 Data

The principal data for the study is drawn from a unique, proprietary panel dataset from one of the three major credit bureaus. It draws information from 285,780 individuals at two points in time (June 2003 and December 2004).[10] The data are from a geographically stratified random sample of individuals. The credit file has information on all data commonly available in a personal credit report. This includes such personal information as individual address up to the location of the census block group, age, and date of birth. It also includes such account information as the number of open accounts, defaulted accounts, etc. Each account file also includes such credit quality variables as current and past delinquencies, size of missed payments, etc. As well, information spans and itemizes account type from mortgages, bank cards, and installment loans to department store accounts. Finally, the credit bureau provides information on individuals' internal credit score.[11] Account files have been purged of names, social security numbers, and addresses to ensure individual confidentiality.

Of the original sample of 586,800 observations, a certain number cannot enter the analysis due to missing data. For example, the $availcredit$ measure is missing in 135,355 observations, $percentblack$ is missing in 48,065, and the credit score measure is missing in 90,865. Once these are removed, there are 401,009 observations.[12] As controls are added in the various tables below, sample sizes fall a bit more.

In order to draw inferences about location-based decision making of lenders, the study exploits the information from the credit file on the locations of residence of the borrowers. With an individual's geocoded census block group, one is able to link a wide variety of information on location characteristics. This paper draws on a set of four external data sources. The first of these is the publicly available U.S. Census 2000.

[10] Specifically, there are 568,000 total observations, including 300,992 drawn in the second quarter of 2003 and 285,808 drawn in the fourth quarter of 2004. Of these, 285,780 overlap and have information available in both time periods.

[11] In order to protect the confidentiality of the data provider, we cannot provide much additional information on the construction of the score. Credit scores in general are inverse rankings of default probability for an individual. Thus, a system that grants one individual a score of 10 and another an 11 has found that the 11 poses a lower risk of nonpayment. To create a score, one regresses default probability on a variety of such credit characteristics as time since last delinquency, amount borrowed, number of accounts, etc. The coefficient of the regressors are then used as weights in determining a "score."

[12] Missing information on credit file information comes from gaps in the original data. Missing information from the demographic files is due to discrepancies between the geocodes from the credit bureau and the census. When a geocode from the credit bureau lies more than a mile from the closest census block group centroid from the census, the data point is excluded. One can also match these remaining points by associating the individual with the closest centroid and run the risk of connecting the individual with an incorrect neighborhood. Nonetheless, the key coefficients on a regression using this methodology are substantively unchanged from the baselines below.

Using the 2000 national summary files, one can link information on block- or tract-level averages of all information drawn from the census long form, including income decompositions, average education levels, country of origin, mobility rates, and more.

The second dataset is the *Uniform Crime Reports* (UCR) of the Federal Bureau of Investigation (FBI). This collects, according to a common standard, information on reported crimes in various categories at a county level. The information is collected on an annual basis, enabling the matching of two sets of crime data to the credit file. Both this and the census file enable one to control for community-level effects that might impact credit issuance decisions.

To capture the role of less regulated consumer credit providers, this study also incorporates information on the prevalence of payday lenders. The data includes geocoded information on the location of more than 25,000 payday lenders across the country. Geocoded files have been provided courtesy of Professor Steven Graves of California State University at Northridge.

The study will exploit a wide range of this information, including the census block group of residence of the card (or other debt) holder.[13] These data have a number of advantages that mirror other studies using individual-level credit card data (e.g., Gross and Souleles 2002). One, this paper can look at various features of borrowing behavior without concern for measurement error common in surveys. Two, it is possible to evaluate fixed effects at the consumer level. To distinguish the data from the Gross and Souleles data, this dataset also has individual location information that allows investigation of differences in credit availability based on local racial compositions.

The variety of data used is reflective of the effort taken to include as many potential location covariates as possible. This allows one to cover a wide range of hypothetical lender practices involving location-based evaluation other than race. Once these other factors are included, one can interpret the race coefficient in a regression with less concern.

To evaluate the issue, one needs both a set of information on individuals' credit and on the neighborhood in which they live. Facilitating this, the credit database includes individual level-geocodes for the census block group of residence. For each of the individuals, this paper matches census and other data based on the provided geocode. This allows one to integrate census block group–level information[14] on population characteristics to determine the racial composition of each of the borrowers' neighborhood. Using census-based geographic areas has some difficulties. For example, an individual who lives on the edge of a census block group may have more in common with the individuals "across the line" than those within the geographic area. Furthermore, a lender may use population characteristics that correspond to areas different than the census definition. The size of the cross section ensures that unless there are systematic tendencies to live at the edge of a census block group, these errors are equivalent to small, normally distributed measurement error, and as such will not impact inference.

[13] A census block group is a cluster of census blocks having the same first digit of their four-digit identifying numbers within a census tract. For example, block group 3 within a census tract includes all blocks numbered from 3000 to 3999. Block groups generally contain between 600 and 3,000 people, with an optimum size of 1,500 people. (Definition from www.census.gov)

[14] In some cases, census data are available only at the tract level. For those cases, we include data at the lower level.

4 Methodology

Since the study is focused on evaluating the role of location-based criteria in the provision of credit, this paper uses census, UCR, and payday lender information to include demographic and location-based information. The method is motivated both by the structure of the credit market and by the nature of the dataset. As most adults know, consumer credit has become increasingly easy to obtain. As a case in point, credit card issuance is commonly done via a (sometimes pre-approved) mail solicitation. Issuers typically use information from credit registries to pre-screen applicants and provide these offers. An example of a possible initial evaluation would be to use credit score alone as a tool for determining which individuals will receive offers for a card of a given type. Once information on the application is returned, issuers evaluate both the information provided on the form as well as the individual's credit history. The underlying question is whether community-level information, in particular on race, is used during either the pre-screen or the credit issuance decision.

What if lenders used information on a potential borrower's neighborhood as a way to determine lending, but used data other than racial composition? One wants to exploit information not only on the individual but also on the area itself. Essentially, the individual is the unit of observation, but acts as a control in the evaluation of an aggregate phenomenon. That is, one wants to understand whether credit issuance in a location (geographically defined) is impacted by race-based criteria. To do this, looking at average lending by demographic characteristics in a location would be inconclusive; a lender could simply provide excess funds to select individuals within a location such that the averages appear to be non–race-based. In this sense, the individual's data serve as a control; based on individual-level credit characteristics, one can evaluate whether lending varies based on the racial composition of a given location.

Notice that the relevance of distinguishing between mean and individual-level differences becomes important here. Consider as a case in point two specific regions. One is predominantly Black and the other predominantly White. These regions also exhibit distributions of socioeconomic characteristics that match current national levels. Thus, the Black area will be poorer and have lower credit quality on average. An issuer that uses mean characteristics to determine whether to market to the entire area could decide to exclude the Black area for purely financial reasons. Changing focus to address individuals, consider figure 1. Notice that the distribution of scores on the X-axis overlaps; there exist some individuals in each area that are nonrepresentative vis-a-vis the means used above. Thus, a purely financial incentive that leads to disparities in access at the community level may not be justifiable at the individual level. An issuer that used the mean criteria simply used profitability characteristics; but in this example it has treated the two individuals of similar characteristics differently based on the racial composition of where they live.[15]

Thus there are two questions. One, once the distributions in figure 1 have been conditioned on demographic characteristics, are there still distributional differences in performance based exclusively on the racial composition of the neighborhood?[16] Two, after accounting for possible individual-level performance

[15] This point is similar in theme to Ferguson and Peters (1995).

[16] A recent Congressional report found systematic performance differences by race. Notably for this study, the report found that Black individuals, conditional on credit score, performed worse than others. Hence, without controls, one will continue to observe

differences, are there still individual-level access differences as illustrated in the figure?

4.1 Single-Equation Systems and Credit Availability

Endogeneity is a well-known problem in the study of credit availability. As mentioned above, it has been a contentious issue in prior work on disparities in lending. In the case here, the problem emerges if issuers adjust credit lines when they expect utilization to change. Then a portion of the observed credit availability change could reflect underlying changes in utilization of credit. Evaluating this behavior can be handled both through use of a particularly rich dataset and through an appropriate instrument.

The data used in the study offer a particularly rare depth of variation in controls. The data section above discusses some of the exceptional information available. Local demographic information from marriage rates to education levels account for systematic differences in utilization driven by life-cycle concerns. Extensive information on local income levels, unemployment rates, and vacancy rates provides proxies for local utilization shocks.[17] Social-environmental factors such as property and violent crime account for additional variation in utilization. The methodology also controls for individual account risk using the credit registry's own measure of credit risk. If issuers attempt to match credit availability to utilization changes, this control strategy should be a strong check against endogeneity.

Although the data in the study provide ample detail, credit issuers themselves must trade off parsimony, essentially cost savings, for the benefit of using additional variables to determine availability. When credit applications are taken, using credit cards as an example, the issuer has direct information on the borrower's age, self-reported income, employment status, household location, and social security number, which is used to acquire credit agency information on the performance and quantity of other credits. In attempting to answer the question of whether issuers use a race variable, one should find evidence across the range of possible specification choices chosen by the issuer. The data available for this study include most of the information contained in the issuer information set,[18] enabling one to check whether racial composition coefficients vary across the range of possible specifications.

The supply proxy itself is potentially an issue. The mortgage literature has used individual accept/reject decisions (see equation 1, above) as its proxy for supply. Of course, this has left open questions regarding both unmeasured demand, in the form of potential applicants who never make it through an application, and unmeasured availability, in the form of willingness to provide loans that were never requested. Consumer revolving credit avoids many of these problems. For example, Gross and Souleles (2002) use the credit limit from individual card accounts as their supply proxy and the utilization on the account as the demand proxy. The basic argument is that these reflect both the willingness of the issuer to provide credit and the actual demand of the consumer. While in principal the issuer may be willing to provide additional credit

distributional differences by neighborhood. The Congressional report, however, did not directly evaluate the question in this paper, nor did it assess whether the distributional differences could be accounted for with non-race factors. The appendix to this paper includes an analysis of individual-level performance measures and finds no qualitative difference in results.

[17]The appendix includes information on a range of additional proxies.

[18]The data being used do not include individual-level information on employment status or income. In their place, block group level information on employment and income is used as a proxy.

and the user may wish to use more debt, for analysis of these issues these proxies are far superior to those used in the mortgage literature. This study uses the sum of credit lines, along with the residual available credit, as a measure of supply, and uses utilization to reflect demand. By using the sum of credit lines, we sidestep issues of substitutability across lines that would occur with individual account analysis. Residual available credit measures willingness to supply credit conditional on current conditions – including existing debt stock. To understand why this is a valuable measure, consider two individuals with identical credit histories, ages, etc. who have $10,000 credit lines. One of these uses $2000/month on a credit card for company travel purposes. A rational issuer would increase the credit line of the individual with the expense account charges; otherwise, her effective credit limit for personal expenditures would be only $8000. As well, many individuals experience growth in earnings, and thus ability to carry debt, over time. Issuers can thus use successful payment of prior debts as evidence of ability to carry higher debt levels. Most likely, both the limit and available credit variables are "supply" variables. This paper uses both as potential proxies.

Single-Equation Systems

First, this paper looks at patterns on revolving credit usage. As discussed, credit can be extended (supply) through card offers and through increases in existing credit lines.

$$availcredit = totalcreditline * (1 - utilizationrate).$$

This paper evaluates the relationship between race characteristics of a neighborhood and credit availability.

Here it looks at some other social factors of available credit with one of the following specifications:

$$availcredit_i = \beta_0 + \beta_1 percentblack_j + \beta_2 X_i + \beta_3 percentblack_j * X_i + \beta_4 Y_j + \varepsilon_i, \tag{2}$$

$$Limit_i = \beta_0 + \beta_1 percentblack_j + \beta_2 X_i + \beta_3 percentblack_j * X_i + \beta_4 Y_j + \varepsilon_i, \tag{3}$$

where X includes various components of credit history as well as an individual's age, and Y includes census block–level income, square of income, racial composition, and other demographic variables. This paper also includes interaction terms for credit history and community-level race variables. Recalling that data are available at different levels of aggregation, with counties the largest aggregation in most cases, the regression includes county-level fixed effects where possible. Errors are clustered at the block group level. One can interpret the coefficients as the responsiveness of available credit to a change in the independent variables. Thus, excluding any view of the demand side, one can view β_1 as the change in available credit due to a 1% change in the Black population in area j. In the results section below, this paper will discuss a number of specification variations — primarily modifications of the vectors X and Y.

Notice that an individual's credit score variable appears on the right-hand side of the equation above. That is, the effort is not to identify disparities in the calculation of the score itself. Credit scores are calculated by many entities, and while one cannot rule out the use of race in the determination of a score, scoring systems are well-known aggregations of individual credit histories. This paper focuses instead on the provision of credit, conditional on given credit quality. There are, of course, some issues of endogeneity here.

In addition to the causal chain implied by equation 2, one could imagine argument for an impact on credit scores as a result of an increase in individuals' credit lines. Thus, the single-equation approaches could very well be subject to the critique that the specification is simply picking up systematic social differences in credit demand. If African Americans systematically use a greater proportion of (evenly provided) credit, one could generate negative coefficients on β_1 and β_3, above. The results here will only be as good as the quality of the supply proxy. To the extent that they represent the supply curve, magnitudes will not differ much from a correctly specified simultaneous system.

4.2 Multi-Equation Systems and Instrumenting with Social Factors

In addition to relying on a large set of controls, this paper uses an instrumental variables approach incorporating instruments that encompass plausible demand variation via "keeping up with the Joneses" effects. These instruments are discussed at greater length below. As a number of authors have emphasized, credit access is a function of both issuer's decisions on availability of credit and individual's choices on quantities to use. There is anecdotal evidence that increased credit lines, even for individuals without notable constraints, leads to increased use. This might be due to shifting from existing credit lines to others, or may reflect actual increases in use. Including a simultaneous system allows one to incorporate this possible effect. Similarly, increases in use may signal to issuers increased willingness or capacity to take on credit, and thus may lead to larger lines. Issuers can increase credit lines or offer new cards to encourage use and individuals can request line increases or order new cards. As above, one could look at the utilization as follows:

$$utilization_i = \gamma_0 + \gamma_1 percentblack_j + \gamma_2 X_i + \gamma_2 Y_j + \gamma_3 Z_j + \varepsilon_2. \tag{4}$$

One can look here at both components using the follow system of equations:

$$\begin{aligned} Limit_i &= \beta_0 + \beta_1 percentblack_j + \beta_2 X_i + \beta_3 Y_j + \beta_4 utilization_i + \varepsilon_1 & (5)\\ utilization_i &= \gamma_0 + \gamma_1 percentblack_j + \gamma_2 X_i + \gamma_3 Y_j + \gamma_4 Z_j + \gamma_5 availcredit_i + \varepsilon_2. & (6)\end{aligned}$$

Equation 4 and the system (5-6) mirror those that have been used in the literature to date.[19] Conditional on an appropriate choice of instruments, one can get an unbiased estimate of β_1, as desired, using two-stage least squares. To obtain this desired result, the standard challenge is to find a suitable candidate for Z.

Instrumenting with Social Factors

Central to two-stage estimation is the specification of appropriate instruments. In this case, one is looking for an unbiased measure of an influence on credit supply. To obtain this, one must specify a set of excluded instruments that are plausibly correlated with utilization but not with availability of credit.

[19] See Phillips-Patrick and Rossi (1996) and Yezer et al. (1993). The argument for including quantities as independent variables is broadly that issuers may include their expectations of utilization changes, as proxied by current levels, in their credit decisions. This may not be fully captured by the set of other covariates. Similarly, borrowers who desire a particular buffer stock of available credit may adjust utilization as available credit changes. While there are relatively straightforward interpretations of the two variables as 'supply' and 'demand,' this paper uses the variables themselves to maintain clarity that the variables are proxies and the system, lacking price information, is not a classic supply and demand one.

First, this paper points to the literature originating with Veblen (1899) and continued in mid-century by Duesenberry (1949). Their well-known works argue that individuals look not only internally to make consumption decisions but also at the consumption behavior of others around them. In modern economics, this has been somewhat formalized as "keeping up with the Joneses" preferences. Under this type of preference structure, agents care not only about their own consumption, but also about some function of the consumption of others.[20] Among others, Dybvig (1995) and Harbaugh (1996) have looked at variations of the same theme with respect to consumption habits. Formalization of preferences that incorporate actions of others is now quite widespread. Surveys of the literature are available in Durlauf (2004) and Soetevent (2006). Focusing on the component of the literature that relates social factors and spending decisions, recent examples include a variety of works: Basmann et al. (1988) show that utility maximization formulations work quite well in describing patterns of commodity expenditures in the U.S. after the Second World War as long as Veblen-style consumption is accounted for. Bagwell and Bernheim (1996) explore theory to explain when Veblen effects can exist and suggest criteria to test for its existence. Bowles and Park (2005) argue that Veblen effects are present in data on patterns of work; they find work hours to be greater in countries with higher inequality.

Based on the claims of this literature, one would want an instrument that is a measure of the income of others in one's reference set. Broadly, one might want to capture the influence of seeing someone from the neighboring town pull into the mall in a luxury car, or of passing someone at work carrying a designer bag. In the case of this paper, one wants to be particularly careful not to include income of others that may be used by credit suppliers. In particular, it is possible that a lender uses the income profile of the neighborhood in establishing credit limits. Akin to using community-level mean statistics on other types of traits, a lender may decide that the wealthy areas confer such benefits as increases in home values that transfer to an increased ability to repay debt. In order to account for the lender's desire to control for local income characteristics, an appropriate instrument may be the income of *surrounding* areas. A pure evaluation of the keeping-up-with-the-Joneses– type effect looks at the role of the relatively-richer on an individual's decisions. Thus, the paper uses mean income of surrounding areas for those areas that have higher earnings than the borrower's own area.

Specifically, the paper uses two measures. Given an individual's census block group, one references only the relatively higher incomes of the block groups living 1-4 miles from the individual. The second instrument uses the same feature 4-20 miles from the individual. The paper uses two measures of distance to allow for different effects of communities that are "close to home" and for those that are further away, but still within a range that can lead to some degree of regular interaction. For example, the first area may correspond to communities with whom an individual interacts at the local school, and the latter, groups that can be observed in the workplace or in a nearby mall or shopping venue. Whether a close neighbor owns a Lexus or a stranger in the mall drives a Mercedes may impact individuals differently. An additional benefit

[20] Recent research in sociology also supports the ideas of Veblen and Duesenberry. Some (see Marmot 2004) even find that health and lifespan are impacted by social standing. See Gali (1994) for a formalization of "keeping up with the Joneses' preferences." He posits that individuals use a utility function: $U(c, C) = (1-\alpha)^{-1} c^{1-\alpha} C^{\gamma\alpha}$, where c is individual consumption and C is average community consumption.

to using the two measures is that the paper can take advantage of common overidentification tests.

This measure proxies for the Veblenesque consumption behavior— i.e., an individual's own consumption is some function of the consumption of others — but without the influences of the immediate proximity areas.[21] Defining a reference space, however, is nontrivial. An argument below is that the precision is not critical once one excludes the area that may be used for supply choices. This argument is buttressed by the fact that this paper does not use this type of social theory to estimate the specifics of individual spending behavior as a function of others (the econometrics for this type of estimation are explained in Manski 1993 and Brock and Durlauf 2001). Instead, it uses the now–well-established connection between the actions of others and human behavior as justification for the excluded instruments.[22] This literature has found, in a myriad of contexts, that individuals base their decisions on the behavior of others.

With both instruments, the exclusion restriction is that they are uncorrelated with issuers' decisions on credit lines. While Veblen, Duesenberry and others have suggested that individuals are influenced by the behavior of those in their reference set, it does not appear that a credit issuer would care about the income levels of neighboring areas or the country of origin of individuals in an area. However, a credit issuer may use information about the community if it impacts default rates. In fact, in June of 2007, New York's attorney general, Andrew Cuomo, accused a "significant number" of lenders of setting loan rates based on the school of a borrower.[23] The null hypothesis is that credit issuers use individual- as well as some community-level information to determine the provision of credit but do *not* use racial information.[24] The assumption that issuers use some community information makes the instrument choice more difficult. Had one specified that the issuer used *no* information on communities, it would be simple to select any community-level variables as instruments.

Along with determining the role of race, one can assume that credit issuers may be using a range of other such location-based factors as crime rates, income levels, and vacancy rates. As such, this paper takes these to be included instruments. Essentially, the claim is that credit issuers that might consider neighborhood characteristics of an individual (e.g., percent Black) would not consider the context of individuals who live in other areas. That is, the percentage of minorities who live a mile away from the card applicant would not be a factor in the credit issuance decision. However, demand, based on the sociological arguments above, will be correlated.

[21] In measuring Veblenesque consumption behavior, one needs to know the consumption patterns of people in a reference group. In this paper, information on income and other factors from an individual's own immediate area are used in the evaluation of discrimination. One would want the information on the keeping-up-with-the-Joneses effect to be drawn from a different area. By choosing the surrounding areas, one can nonetheless assume that an individual references her spending off of those in nearby areas as well.

[22] In the nomenclature of the social interactions literature, we will be using contextual effects defined by the geography of individual's home as excluded instruments.

[23] *New York Times*, June 19, 2007.

[24] In fact, the paper evaluates a number of nulls. The first column of a number of the tables is essentially the null that the lenders uses no information on community-level factors. A rejection of the null of no factors at all allows us to move to the more realistic setting described here. To be clear, evaluation of the hypothesis is reliant on the instruments being valid — this is addressed below.

5 Interpretation of Results

Broadly, the attached tables find a significant positive coefficient on the $percentblack$ variable and a significant negative coefficient on the $percentblack * creditscore$ variable. The net effect is uniformly lower access to credit in Black communities. A few comments are useful at the outset. One, the coefficients are largely unchanged across a very wide range of specifications, and across both single and multi-equation systems. The consistency of results across the range of specifications addresses the concern that since racial fractions are highly correlated with many other tract characteristics, multicollinearity issues can infect the regressions and lead to spurious inference on a single regressor. Thus, a study which found only limited specifications with a significant race coefficient would be particularly weak evidence. Two, while the study includes many variations of a baseline specification, the parsimonious ones are more likely representative of the information used by issuers in the credit decision. Given cost constraints, using all possible variables seems an unlikely method. Three, the similarly of results across single and multi-equation systems suggests that the supply proxy is a good one; that is, it does not appear to be biased due to simultaneity. This marks a distinction from the simultaneity debate in the mortgage literature in that there is clear evidence here that the supply proxy is a good one.[25]

Numerous studies on mortgage lending have found negative correlations between access to credit and race/neighborhood racial composition; this study takes advantage of a unique dataset and finds similar patterns in consumer lending.

5.1 Single-Equation Results

Table 6 shows results from equation (2) above. Column 1 regresses available credit on percentage Black and the individual's credit score. As expected, credit score is positively and very strongly related to the amount of available credit. The race variable is negatively related to the amount of available credit; a 1% increase in the percentage of African Americans in an area corresponds to a reduction in available credit of \$123. Moving from an 80% majority White to 80% majority Black area reduces credit by an average of \$7,357. Moving to column 2, one can see the interaction of the race and credit score variables, $percentblack_j * creditscore_i$. This allows the inspection of the nonlinearity in credit availability (for the time being, ignoring utilization decisions). The percentage Black variable becomes positive and the interaction term is negative in this case. To interpret the magnitude here, consider a credit score of about 600; each unit change in the percentage of African-Americans leads to an increase in credit of \$131 from the percentage Black variable and a reduction of \$246 from the interaction term — a similar net magnitude found in column 1. The nonlinear term suggests that the race "penalty" is greater for individuals with better credit histories. A plausible interpretation of this effect is that issuers consider "bad" credits to be universally "bad," independent of race. As credit quality increases, Black individuals with "good" credit receive relatively smaller advantages for the improved performance. The remaining columns explore the

[25] While the empirical results from the Boston Fed Study were not overturned based on the endogeneity concerns, the nature of the data available at the time (and of mortgages) simply did not allow the type of analysis presented here.

robustness of these findings to the inclusion of other community-level variables from education and marital status to language use and crime rates. Key coefficients remain essentially unchanged. Column 3 introduces an age variable, which has a significant and positive impact on available credit.

To address the possible concern that the coefficient on the $percentblack$ variable is biased due to an omitted variable, moving from columns 4 to 8 progressively adds control variables of various types. The per capita incidence of violent crime (column 4) is negatively associated with credit availability, although insignificant. Column 5 shows the percentage of male and females who have obtained more than a high school diploma; both are positively related to credit availability. A higher percentage of married men and women is also correlated with available credit (column 5). Column 6 shows the percentage of foreign-born in the neighborhood is statistically significant and is correlated with reduced available credit. Finally, the percentage of high income individuals positively correlates with available credit, while the percentage of low income individuals is not significant.[26] As mentioned above, the study includes essentially the same data used by issuers in the determination of credit, and while marketing departments may draw on additional external information, the range of variables included here show that the $percentblack$ coefficient is highly robust to specification choice.[27]

Limits

Looking at an alternate view of credit provision, total credit limit produces similar insights (see table 7). The first column again shows only the racial percentage variable and the credit score, finding a drop of $134 in limit for each percentage point drop. Results are analogous when one moves to column 2. Here again one finds a similar penalty in the nonlinear term; an individual with a 600 credit score suffers a $222 drop for each percentage increase in the composition of Blacks, which is then offset by a $70 increase. The implication is that even predominantly non-Black areas see individuals facing large changes in credit limit for small increases in minority populations. As other controls are included, the percentage Black variable increases in size, while the interaction term's magnitude is reduced. The best intuition for this is that the various community-level controls both reduce the influence of the nonlinearity (the "rate of change") and affect the average levels of total credit. Control variables in this table have similar coefficients as in the prior table.

5.2 Instrumental Variables Results

As discussed in the above section, this paper analyzes the role of race in credit limits using a two-stage least squares approach (see equations 5 and 6 above). This paper subdivides the results in table 8 as follows. The first six columns include the two Veblen-Duesenberry instruments discussed above. Both are an interaction of aggregate income in the surrounding census blocks, with an indicator for the surrounding blocks having higher income than the immediate area. The first includes areas 1-4 miles from the individual, and the second, areas 4-20 miles. The final two columns include each instrument in isolation. All specifications

[26] These results are suppressed for space considerations, but are available in an unpublished appendix, on request from the author.

[27] An appendix, available on request from the author, adds specification variations to address a range of additional concerns. No significant differences are found from those reported here.

include fixed effects at the county level and are estimated with robust standard errors.

In each case, the key variables are the same as above: the percentage of African Americans in a neighborhood and the interaction term $percentblack_j * creditscore_i$.[28] The coefficients on $percentblack_j$ and $percentblack_j * creditscore_i$ are similar in magnitude and sign to those in table 6. Results are illustrated in figure 2. At low levels of credit, credit availability is quite low, but not distinguished greatly by race. As credit quality increases, the gap, controlling for the various characteristics mentioned in the study, grows quickly.

A number of test results are presented below the table. The overidentification test statistic (Hansen J-stat) is well within the do-not-reject ranges. As well, the Kleibergen-Paap LM test strongly rejects the null of underidentification.

6 Discussion

The results here imply a form of differentiation in both the availability-only equations and full simultaneous system. However, since the implication is not a small one, one can look deeper into the data for an understanding of how much this effect matters and for a better appreciation of how sensitive the results may be to various factors. Following a discussion of economic relevance in subsection 6.1, there is a dissection of the population into different score categories in order to understand which groups might be facing the greatest challenges. The second subsection (6.2) investigates the consequences of differences in financial education on estimation results. The next subsection (6.3) looks at issues of alternate sources of finance, continuing in subsection 6.4 with a discussion of the robustness of the instrument choices to variation in geographic area. Subsection 6.5 discusses some limitations of the analysis.

6.1 Economic Relevance

Many owners of credit cards use far less credit than would be allowed by the lender; in fact, for many there may possibly be no foreseeable event for which they would even contemplate using the credit. Given this, can one claim that race-based disparities in lending have a clear economic impact? In the case of mortgages, it has a clear economic harm.

This paper motivates the relevance in two ways. The first is based on the selection involved in creating the data. By definition, the data contain only individuals with a credit history; those without are those that either chose not to obtain credit at all, or made do with credit supplied either by the nonbank sector (payday lenders, etc.), by friends and family, or by some other nonreporting financial institution. Prescott and Tatar (1999) and Rhine et al. (2001) provide evidence that the underbanked, a category broadly encompassing those without checking/savings accounts and/or credit cards, are predominantly from poor and minority

[28] We abstract here from the endogeneity of location choice. One might imagine that individuals choose where to live based on the availability of credit — particularly in the mortgage case. In the credit card case, we hypothesize that the decision process for credit issuance is sufficiently opaque to card users that determination of credit supply functions for potential new residences is difficult or impossible.

areas. Notice that, if true, this will bias the estimates toward zero; including a disproportionately minority group that has poor credit would increase the evidence of disparities in lending. Without emphasizing the econometric difference here, this paper simply notes that there is a documented impetus toward alternate credit sources when traditional ones are unavailable.

Second, one can view the role of differences in lending across the distribution of available credit. For those with very small amounts of credit, availability restrictions could quite plausibly be binding on consumption decisions. Two tables illustrate that credit constraints can be potentially binding. Figure 3 shows two sets of coefficients on the interaction variable, $percentblack_j * creditscore_i$, for quantiles of available credit from 10 to 90. The blue line shows the results for a quantile regression using controls from the specification in table 6, column 6. This line would suggest that the impact is greatest for those with the most credit; perhaps then the economic relevance is small? To investigate, we add the red line, which uses the log of credit limit as the dependent variable.[29] This reverses the slope of the line — suggesting that there is a difference in access bias on a relative basis, and that the bias is potentially important to those in the range of credit access that could bind with respect to consumption decisions.

One's most direct interpretation of the data is that the strongest race-based disparity is found for scores in a middle category and for individuals with relatively low amounts of available credit. It appears to suggest that once individuals with particularly poor chances of obtaining credit have been screened out (including out of the sample altogether), those individuals with acceptable credit but with small amounts of available credit face the greatest relative access impediments. Recall that this conclusion accounts for the endogeneity of credit availability.

6.2 Age and Financial Learning

A 2002 study from the Federal Reserve Board (Braunstein and Welch 2002) argues that many people in underserved populations may be unfamiliar with components of the financial system. A combination of growing complexity, increases in consumer responsibility, as well as the noted changes in the structure of personal finance to include more individual credit, have contributed to differences in financial literacy. For the purposes of this paper, these differences may translate into differences in understanding about how to build individual credit. Thus, one can imagine that if Black communities have less information on the nature of the credit scoring systems, otherwise credit-worthy individuals may have systematically lower scores.[30]

However, this is a phenomenon that will not be captured in the attached analysis by the inclusion of a score variable. Consider two similarly responsible individuals, one of whom knows nothing about credit scoring systems used by credit issuers. The more knowledgeable individual will take out a credit card, even one with a very low limit, use it regularly, and make reliable payments. As many are aware, even low-volume transactions that are paid on time appear on credit histories as timely payments. The less informed individual may use his or her card irregularly, but make payments on time. The latter individual will have

[29] Results for both sets of specifications are available from the author upon request.

[30] Worthington (2006) finds that race and income are both strong determinants of financial literacy. Rhine et al. (2001) and Prescott and Tatar (1999) find similar results.

a lower score, even though his/her behavioral characteristics vis-a-vis credit worthiness are identical to the other's. Extending the example, if one compares two individuals with identical scores, but without this noted difference in understanding, the one with less education is the *better* credit risk. Since education levels are unobserved in the data, one cannot fully measure the bias.

To account for the impact of this difference, one can incorporate an aging effect. One expects that there might be systematic differences across communities in financial literacy that correlate with race demographics; however, one expects that these differences are a function of the time needed to accumulate the necessary information, not a difference in the fundamental capacity to understand. As such, this difference will appear in the interaction between the age variable and the percentage Black variable; learning will take place, but the age-controlled amount of information will possibly be different across communities.

Table 10 shows the effects of these age-race interactions, and figure 4 shows predicted values along the age distribution for Blacks and non-Blacks. In column 2 of this table, we find that the interaction of age and percentage Black is strongly significant. However, the effect of this interaction appears to be nonlinear, as shown in column 3 and in the figure. What one can see from the figure is that there are age effects. Non-Blacks show increases in credit limits up to age 40 or so, then a decline.[31] For financial learning to have impacted the results and created the spurious impression of differences in access, one would need a pronounced inverted U for the Black curves seen in the figure; in particular, it would need to lie to the right of the non-Black curve. One does not observe this pattern; even with the aging effect present (and clearly observed), there are still significant race effects in the data.

6.3 Nontraditional Lending

A wide array of recent research has focused on the recent expansion of nonbank lenders. So-called payday lenders[32] are institutions that lend money on a short-term basis. The typical procedure involves leaving a post-dated check, timed to coincide with the subsequent paycheck, in exchange for a loan. When the loan comes due and is repaid, the shop returns the uncashed check. Lenders charge interest rates around 15-20% for a two-week loan; over the course of a year, the rates amount to 300% or more. As the institutions are regulated on a state-level basis, and data collection is sparse, there is incomplete information on the scale of existing business. One estimate (from 2003) is that about 10 million U.S. residents take out such loans each year (Robinson and Wheeler 2003) with a volume of approximately $40 billion. The common statement is that they are now more prevalent than McDonald's. Not-for-profit advocacy groups have claimed that they are targeting minority and poor areas (Center for Responsible Lending) and the debate on their role and potential regulation has become widespread.

Regardless of the motivation for these lenders' location choice, two recent research projects (Prescott and Tatar 1999 and Rhine et al. 2001) provide evidence that the underbanked are predominantly from poor

[31] The most plausible explanation for this decline is a generational effect. Those above 40 became exposed to credit cards much later in their own lives than younger individuals due principally to the relatively recent introduction of cards. As a result, many have shorter credit files and a higher probability of low use.

[32] Other types of lenders exist as well, including pawn shops and rent-to-own establishments. We focus on payday lenders as they are the most direct equivalent to credit cards; that is, both are unsecured lines of credit.

and minority areas. The implication commonly drawn is that lack of access to traditional financial service products, coupled with volatile consumption needs, drives the most risk prone into the arms of high-rate lending options.[33]

This paper includes a short analysis on the relationship between payday lenders' availability and traditional credit patterns. Broadly, this paper has found differences in access to credit that depend on racial composition of a neighborhood. If payday lending were to have an impact here, one would expect that lenders that intended to differentiate credit could offer less in areas with more payday lending. This would draw on the fact that payday lending is a type of credit and serves, for some individuals in some areas, as a potential substitute. If it acted as a pure substitute, one would expect to see a negative coefficient on the payday stores variable. We can see this negative coefficient in table 11, column 2. Column 1 repeats the table 8, column 6 specification from above, and column 2 adds a measure of the number of payday lenders with a three-mile radius of each individual's census block group.

Similarly, credit differentiation should show an increase in the magnitude of the key coefficients once one accounts for the potential placement of payday stores in low-quality credit areas or minority areas. This can be seen in columns 3-5. While the interaction of the payday stores variable and race or payday stores and credit quality is not significant, the payday stores variable interacted with score is significant. Key cofficients remain essentially unchanged and highly significant across specifications.

6.4 Size of Reference Region

Within a Duesenberry/Veblen framework in which individuals base their consumption decisions on those of people around them, one is concerned with the question of whom they base their individual consideration. In much of the social interactions literature, reference groups are assumed to be a relatively small geographic or social sphere. The largest in the literature tends to be a Public Use Microdata Area (PUMA), an area of up to 100,000 individuals. However, it is more common to use school classrooms, places of work, or census blocks as the area of reference; in each case, the assumption is that the particular decision of consequence to the study is mediated by behavior of other people in the reference group.

This paper posits that credit demand is influenced by individuals in the area of reference used. Do individuals decide whether to buy a bigger car, an iPod, a new cell phone, etc., based on whether their next-door neighbor does so, or based on some other criterion? Many advertisers are certainly convinced that product demand is based on TV viewership – not just local word of mouth. As the goal of this paper is somewhat less lofty than a pure identification of the degree of interaction in credit decisions, one can permit a degree of misspecification in the instrument. The key metric in assessing the validity of the instruments is whether they are correlated with utilization but uncorrelated with limits; thus one needs to be confident that the chosen area both captures some of the social influence of one's neighbors and is orthogonal to whatever

[33] Skiba and Tobacman (2007) come to the conclusion that since many payday loans are repeat customers, this volume is unlikely to be driven by temporary shocks to consumption need. However, this is a controversial statement; one could as easily argue that once an individual faces a shock and is forced to take out a loan, this leads to a drop in asset wealth and an increased likelihood that an even smaller shock will lead to future borrowing needs.

spatially based income characteristics that a lender may be using.

The primary metric (as discussed above) is a 1-mile radius around each individual — with the demand-only area of reference being the 1–4- and 4–20-mile bands from the center. This essentially assumes that credit issuers may be using local income characteristics to make lending decisions; however, individuals may be influenced both by those in the immediate vicinity and by those they pass at the mall, on the way to work, etc.

To be confident that the right measures are being used and to fail overidentification tests, one would want that excluded instruments include the immediate vicinity – indicative of the fact that they may be included in the availability function. One can look at using a census block as the unit of reference and at a demand-only reference band encompassing 1–4 and 4–20 miles from the individual.

The results are relatively straightforward; the size of the reference region appears to play a relatively small role. The final two columns of table 8 include reference bands of 4–20 miles and 1–20 miles alone. Mechanically, this amounts to including only a single instrument in each case. Notice that the coefficients remain largely stable across the columns. Using the 4–20-mile radius instrument alone leads to inability to reject the null at the 10% level. One can broadly interpret this as the demand effect becoming somewhat more diffuse.

6.5 Limitations

Any empirical study of this type will have a number of limitations. In the case here, the most notable is the absence of price information. Given the findings of Edelberg (2007) that there are systematic disparities in price correlated with race, it is unlikely that inclusion of price will change the qualitative nature of the results here. Higher prices for minority communities should in theory lead to lower utilization rates, but there is little reason to believe that it would lead to lower credit limits conditional on credit quality. That is, a profit-maximizing firm should be more willing to provide credit at high rates to equally qualified applicants.

The second notable limitation has been discussed throughout the paper. The data, though much more comprehensive than that used in prior studies of this type, do not specify precisely the set of covariates used by lenders in marketing or lending decisions. This makes the econometric task a more challenging one. One must rule out a very wide range of plausible specifications before coming to a conclusion on availability patterns.

Third, given the degree of regulatory scrutiny over the credit decision itself, one suspects that if any disparity exists in the provision of credit, it likely originates in the pre-screening (marketing) efforts. However, the methodology used is not able to distinguish explicitly between these functions. As such, the test used is essentially for the presence of race information in the screening process at one or both stages. This leads naturally to the question of legality, which this paper has explicitly avoided.

Finally, if issuers are simply profit seeking, and race is correlated with profitability, why shouldn't a bank be able to condition credit limits on race? Or if race isn't correlated with profitability directly, why shouldn't issuers be able to use race to proxy for other factors that are related to profit? There are legal precedents that provide some guidance here, though the paper won't address them in detail. The most relevant case is out of the U.S. Supreme Court *Wards Cove Packing v Antonio*, 490 US 642 (1989). This case outlines a three-step criterion for the assessment of disparate impact. "Disparate impact" refers to the ex-post evaluation of differences in credit access; that is, the differences that may arise from any part of the issuance process. There are more strict guidelines for the underwriting decision itself, among which is the documented rationale for any denial of credit. The first criterion in the *Wards Cove* case requires the identification of the presence of a "substantial disparate impact." If met, the second criterion shifts the burden of proof and requires the credit issuer to explain the legitimate business interest motivating its method of credit availability that led to the disparate impact. If the second criterion cannot be met, the third requires that there be an equally effective but less discriminatory option available. Only if the third test is reached and not met could a court find that there had been a problem in the issuance of credit. Whether this holds true in the circumstances examined here is beyond the scope of this paper.

7 Conclusions

The two couple decades have seen a wealth of research on the role of race in mortgage lending decisions. A relatively broad consensus in the literature is that in spite of federal legislation prohibiting discrimination in the home-buying process, minorities nonetheless continue to face significant barriers to buying homes. Contributing to the difficulties faced by minorities are systematically worse credit histories at the time of a home purchase decision; worse credit means higher payments or no loan at all. Enter credit cards. Most adults in the United States are now somewhat familiar with the use of credit cards and the notion that regular payment improves credit scores. Building up the good credit history necessary to buy a house is now almost inextricably connected to the prior reasonable use of credit cards. Credit histories are also now used in determination of auto insurance rates and in job applications.

Access to consumer credit, both in volume and number, is negatively related to the racial composition of an individual's neighborhood. The policy implications are parallel to those in the mortgage literature. Conditional on the finding of differential access to credit cards, long-term differences in home ownership rates is suggested for the reasons discussed above. As well, the lack of access has another, more pernicious effect. While credit card interest rates are exceptionally high compared to collateralized credit such as mortgages, they are nonetheless quite low compared to the growing payday loan market, where borrowers often go when other loan avenues are closed. Payday lenders often charge annual interest rates upward of 300%.

Access to consumer credit, more so than to mortgages, is a starting point on the modern financial ladder.

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Figure 1: Neighborhood credit distributions

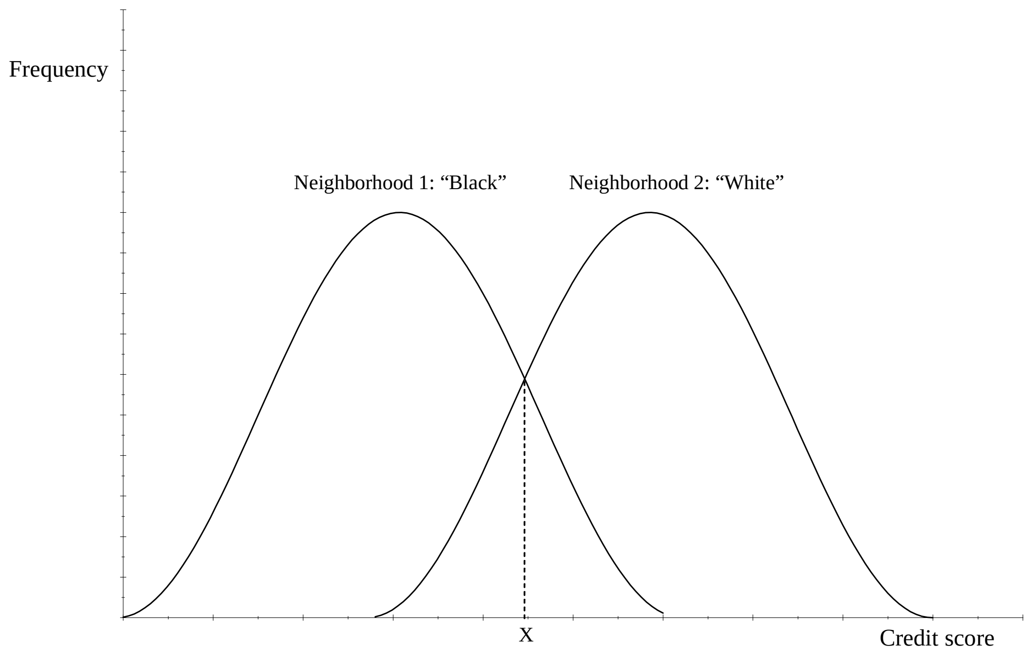
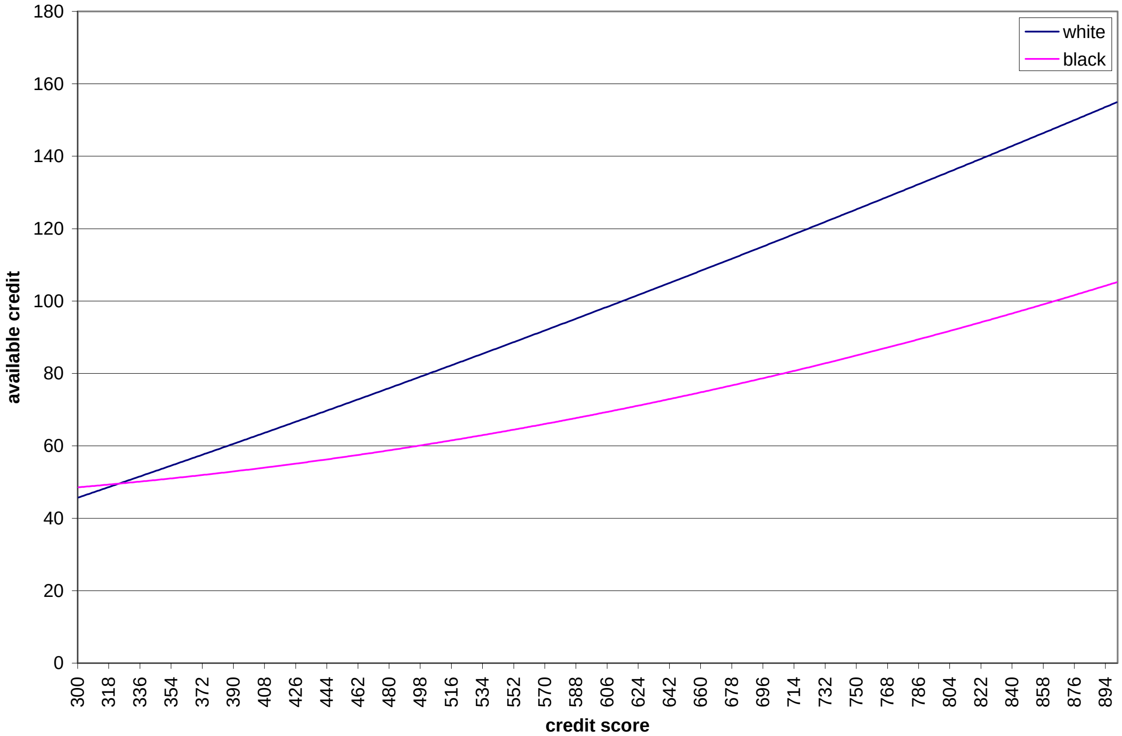


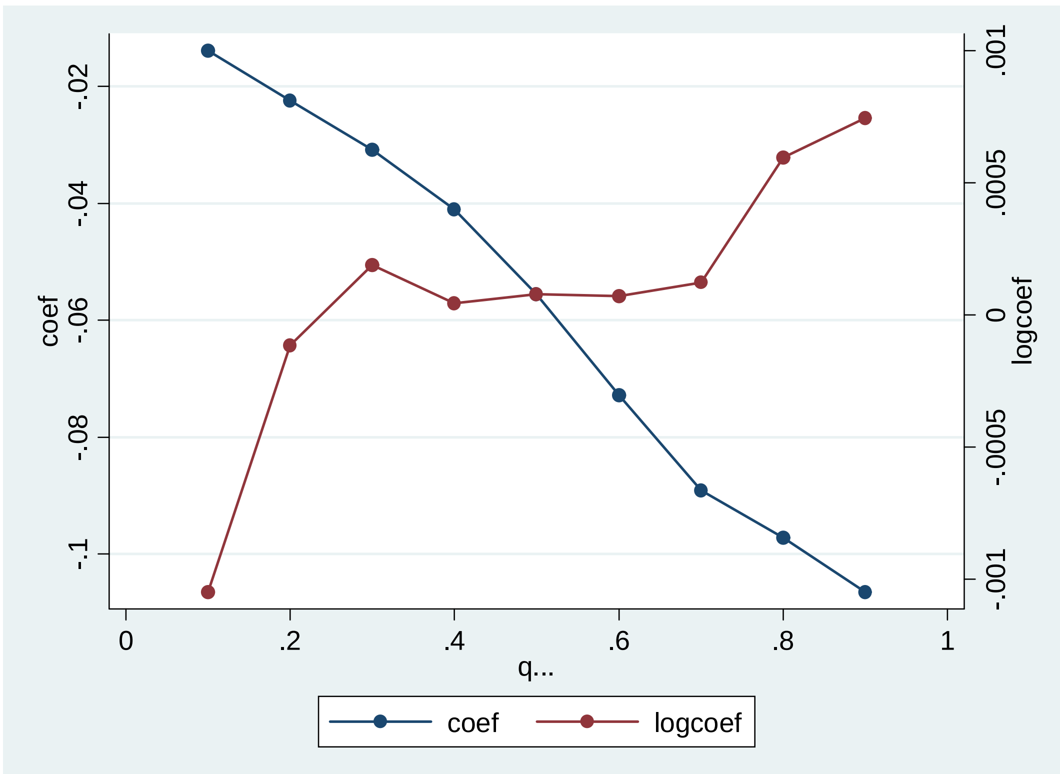
Figure shows two stylized credit score distributions from two neighborhoods that are predominantly "Black" and "White."

Figure 2: Available credit vs. credit score



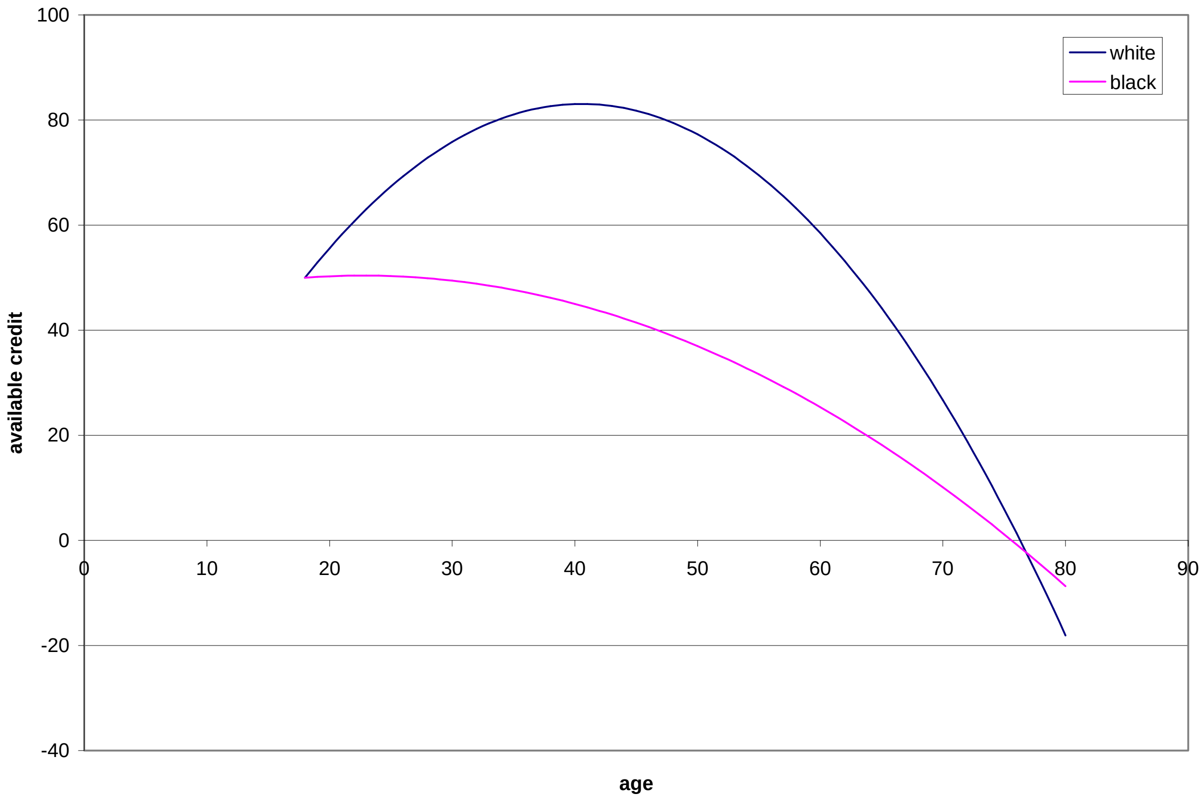
This figure shows a plot of implied available credit by credit score for an individual in a 100% White neighborhood and an individual in a 100% Black neighborhood. Values are calculated based on regression output in column 3 of table 8.

Figure 3: Quantile regressions



Blue line shows the coefficients of a quantile regression of available credit on a range of controls (see column 3 of figure 8 for list). Red line shows the coefficients of a quantile regression of the log of available credit on a range of controls (see column 3 of figure 8 for list).

Figure 4: Credit vs. age



This figure shows a plot of implied available credit by credit score for an individual in a 100% White neighborhood and an individual in a 100% Black neighborhood. Values are calculated based on regression output in column 3 of table 11.

Table 1: Introductory data relationships

Panel A - Univariate regressions of months since last delinquency on selected variables						
months	married M	married F	secondary-ed M	secondary-ed F	household inc	% Black
coefficients std errs	5.939 (.398)***	5.625 (.382)***	5.525 (.231)***	5.794 (.264)***	.1226 (.005)***	-4.742 (.192)***

Panel B - Correlations between selected explanatory variables						
	married M	married F	secondary-ed M	secondary-ed F	household inc	% Black
married M	1					
married F	.8812	1				
secondary-ed M	.2394	.2169	1			
secondary-ed F	.2053	.202	.947	1		
household inc	.3241	.2942	.7502	.737	1	
% Black	**-.4465**	**-.5153**	**-.2857**	**-.2199**	**-.2845**	1

Table 2: Credit across race quintiles

availcredit		
Race quintile	Mean	SD
1	67.113	122.399
2	46.052	81.742
3	37.984	76.267
4	32.858	69.262
5	27.460	63.488

score		
Race quintile	Mean	SD
1	662.366	180.616
2	600.261	193.901
3	564.915	195.714
4	538.160	194.637
5	509.338	186.694

# accounts		
Race quintile	Mean	SD
1	13.259	12.126
2	10.779	11.467
3	9.772	11.265
4	9.160	10.984
5	8.284	10.439

limit		
Race quintile	Mean	SD
1	82.064	148.447
2	53.286	100.171
3	42.741	90.731
4	37.060	81.100
5	30.773	76.538

util %		
Race quintile	Mean	SD
1	37.171	35.223
2	44.458	38.233
3	49.485	40.310
4	52.374	43.151
5	56.823	44.536

Note: Quintile 1 consists of areas with <20% African Americans. Quintile 2 consists of areas with between 20% and 40% African Americans. Quintile 3 consists of areas with between 40% and 60% African Americans. Quintile 4 consists of areas with between 60% and 80% African Americans. Quintile 5 consists of areas with >80% African Americans.

Table 3: Variable description and data sources

Variable	Description	Source
	Credit Variables	
limit	Credit limit (in thousands of dollars)	Consumer Credit dataset
util %	Utilization rate	Consumer Credit dataset
# accounts	Number of unique accounts	Consumer Credit dataset
score	Credit score	Consumer Credit dataset
	This is a measure of credit quality largely equivalent to a FICO-score	
availcredit	Available credit (in thousands of dollars)	Author calculations
	Available credit is calculated as total available credit line .	
	minus any current balances: limit * (1-util%)	
util $	Utilized credit (in thousands of dollars)	Author calculations
	Utilization is the product of the utilization rate and total credit lines.	
	Demographic Variables	
% Black	Percentage of population with race of Black or African American	Census 2000 Summary File
age	Age of individual	Consumer Credit dataset
age^2	Square of above	Consumer Credit dataset
score * % Black	Interaction of score with percentage Black	Consumer Credit dataset
(score * % Black $)^2$	Square of above	Consumer Credit dataset
public assistance	Percentage of households receiving public assitance	Census 2000 Summary File
foreign-born	Percentage of population born outside the United States	Census 2000 Summary File
income growth (inflation adj)	Inflation-adjusted average income growth by PUMA	2000 & 2005 ACS
% employment	Percentage of population over age 16 listed as employed	Census 2000 Summary File
	Housing Variables	
% vacant	Percentage of housing units that are not occupied	Census 2000 Summary File
% owner-occupied	Percentage of housing units that are occupied by owner	Census 2000 Summary File
% houses w/ mortgage	Percentage of housing units with mortgages	Census 2000 Summary File
median rent	Median rent of specified renter-occupied housing units	Census 2000 Summary File
median house value	Median house value by census block group	Census 2000 Summary File
	Income Variables	
income 10k-15k, etc.	Percentage of households with annual income between $10k and $15k, etc	Census 2000 Summary File
inc 150kplus	Percentage of households with annual income greater than $150k	Census 2000 Summary File
	Income groups are also specified for fourteen ranges of income	
	between $15k and $150k. This information is available upon request.	

Table 4: Variable description and data sources

Variable	Description	Source
	Language Variables	
lang Span	Percentage of households where Spanish is the primary language	Census 2000 Summary File
lang Asian	Percentage of households where an Asian language is the primary language	Census 2000 Summary File
	Crime Variables	
violent crime	Violent crime per capita	FBI Uniform Crime Reports
property crime	Property crime per capita	FBI Uniform Crime Reports
	Educational Attainment	
$>$ HS ed - male	Percentage of male population with educational attainment $>$ HS diploma	Census 2000 Summary File
$>$ HS ed - female	Percentage of female population with educational attainment $>$ HS diploma	Census 2000 Summary File
eq HS ed - male	Percentage of male population with educational attainment = HS diploma	Census 2000 Summary File
eq HS ed - female	Percentage of female population with educational attainment = HS diploma	Census 2000 Summary File
	Marital Status	
married - male	Percentage of male population over age 15 listed as married	Census 2000 Summary File
married - female	Percentage of female population over age 15 listed as married	Census 2000 Summary File
nonmarried - male	Percentage of male population over age 15 listed as nonmarried	Census 2000 Summary File
nonmarried - female	Percentage of female population over age 15 listed as nonmarried	Census 2000 Summary File
widowed - male	Percentage of male population over age 15 listed as widowed	Census 2000 Summary File
widowed - female	Percentage of female population over age 15 listed as widowed	Census 2000 Summary File
divorced - male	Percentage of male population over age 15 listed as divorced	Census 2000 Summary File
divorced - female	Percentage of female population over age 15 listed as divorced	Census 2000 Summary File
	Instrumental Variables	
GTagginc 1-4 miles	The average income of the surrounding block groups in a 1–4-mile radius with income greater than the immediate area's average income	Census 2000 Summary File
GTagginc 4-20 miles	The average income of the surrounding block groups in a 4–20-mile radius with income greater than the immediate area's average income	Census 2000 Summary File
	Payday Variables	
PD3mile	Number of payday lenders within 3 miles of the individual	Prof. Richard Graves
PD-Black	Interaction of PD3mile with % Black	Prof. Richard Graves
PD-score	Interaction of PD3mile with score	Prof. Richard Graves

Table 5: Summary statistics

Variable	Median	Mean	SD	Variable	Median	Mean	SD
limit	6.100	23.627	46.302	property crime	0.033	0.036	0.018
util %	11.400	27.770	35.493	$>$ HS ed - male	0.522	0.533	0.193
# accounts	10.000	12.677	12.042	$>$ HS ed - female	0.504	0.515	0.169
score	652.851	606.351	165.835	eq HS ed - male	0.269	0.269	0.106
availcredit	12.506	27.012	45.229	eq HS ed - female	0.289	0.290	0.096
util $	1.574	6.582	15.212	public assistance	0.024	0.036	0.037
% Black	0.036	0.127	0.209	married - male	0.588	0.580	0.112
age	46.000	48.207	17.123	married - female	0.540	0.539	0.115
age^2	2116.000	2617.117	1842.198	nonmarried - male	0.293	0.307	0.103
age * race	1.409	5.384	10.146	nonmarried - female	0.227	0.246	0.098
score * % Black	20.589	67.257	114.231	widowed - male	0.023	0.026	0.016
score^2* % Black	12887.640	43426.340	80442.260	widowed - female	0.100	0.105	0.048
income 10k-15k	0.135	0.157	0.102	divorced - male	0.084	0.088	0.036
income 15k-20k	0.058	0.062	0.037	divorced - female	0.110	0.111	0.040
income 20k-25k	0.061	0.062	0.032	income growth (inflation adj)	0.167	0.482	2.610
income 25k-30k	0.066	0.065	0.030	employment	0.817	0.809	0.090
income 30k-35k	0.065	0.064	0.027	% vacant	0.053	0.070	0.067
income 35k-40k	0.064	0.063	0.025	% owner-occupied	0.673	0.650	0.206
income 40k-45k	0.058	0.058	0.022	% houses w/ mortgage	0.708	0.699	0.136
income 45k-50k	0.055	0.056	0.021	median rent	0.615	0.665	0.259
income 50k-60k	0.048	0.049	0.020	median house value	112.200	138.333	98.052
income 60k-75k	0.089	0.090	0.030	foreign-born	0.064	0.116	0.132
income 75k-100k	0.103	0.105	0.042	GTagginc 1-4 miles	26.161	29.642	13.167
income 100k-125k	0.097	0.105	0.056	GTagginc 4-20 miles	28.518	31.438	12.305
income 125k-150k	0.042	0.054	0.042	PD3mile	1.000	5.915	9.182
income 150k-200k	0.017	0.026	0.027	PD-Black	0.024	1.011	2.841
income 200k plus	0.012	0.023	0.029	PD-score	662.868	3202.052	5264.233
DNT avg income	21261.230	21516.480	4573.306				
lang Span	0.053	0.115	0.161				
lang Asian	0.012	0.029	0.054				
violent crime	0.004	0.005	0.003				

Table 6: Credit availability regressions

availcredit	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Black	-12.261	13.105	11.316	11.601	20.418	19.059	16.872	18.491
	(.516)***	(1.498)***	(1.619)***	(1.675)***	(1.690)***	(1.707)***	(1.758)***	(1.909)***
score	.091	.097	.101	.100	.095	.095	.094	.093
	(.0005)***	(.0006)***	(.0007)***	(.0007)***	(.0007)***	(.0007)***	(.0007)***	(.0008)***
score * % Black		-.041	-.040	-.041	-.031	-.030	-.027	-.027
		(.002)***	(.002)***	(.003)***	(.003)***	(.003)***	(.003)***	(.003)***
age			.110	.110	.110	.110	.106	.105
			(.005)***	(.005)***	(.005)***	(.005)***	(.005)***	(.006)***
violent crime				-959.008	-1010.030	-1006.920	-834.330	-577.291
				(602.272)	(599.030)*	(598.999)*	(601.523)	(641.613)
property crime				209.221	203.964	202.923	206.180	189.572
				(98.248)**	(97.721)**	(97.717)**	(97.410)**	(107.503)*
education					included	included	included	included
marital status					included	included	included	included
foreign-born						included	included	included
income							included	included
public assistance							included	included
inc growth (inflation adj)							.093	.140
							(.052)*	(.059)**
% employment							.116	4.319
							(2.137)	(2.473)*
% vacant								-.416
								(1.842)
% owner-occupied								3.813
								(1.123)***
% houses w/ mortgage								-1.931
								(1.289)
median rent								.906
								(.567)
median house value								.035
								(.003)***
Observations	365092	365092	323622	303235	303179	303179	286427	241451
R-squared	.082	.083	.094	.093	.103	.103	.108	.111
F-Stat	16143.38	10880.39	8329.338	5159.003	2162.98	2037.849	981.131	746.649

Note: The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Dependent variable is measured in 000s USD. County-level fixed effects included. For brevity, many coefficients are suppressed. "Income" includes percent of population divided into 16 income brackets. "Education" includes percent of population with educational attainment of high school diploma or greater. "Marital status" includes percent of population nonmarried, widowed, or divorced. Full results are available in the appendix.

Table 7: Credit limit regressions

credit limit	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Black	-13.419	7.070	3.666	3.691	14.291	12.503	10.077	11.991
	(.454)***	(1.112)***	(1.297)***	(1.345)***	(1.370)***	(1.391)***	(1.443)***	(1.575)***
score	.089	.095	.100	.099	.093	.093	.091	.091
	(.0004)***	(.0005)***	(.0006)***	(.0006)***	(.0006)***	(.0006)***	(.0007)***	(.0007)***
score * % Black		-.037	-.033	-.033	-.022	-.022	-.018	-.018
		(.002)***	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***
age			.080	.082	.082	.081	.077	.076
			(.005)***	(.005)***	(.005)***	(.005)***	(.005)***	(.006)***
violent crime				-884.869	-904.196	-904.144	-734.297	-539.202
				(581.431)	(578.029)	(577.987)	(583.953)	(622.792)
property crime				200.707	190.789	190.678	190.288	183.436
				(95.638)**	(95.083)**	(95.076)**	(94.916)**	(105.157)*
education					included	included	included	included
marital status					included	included	included	included
foreign-born						included	included	included
income							included	included
public assistance							included	included
inc growth (inflation adj)							.043	.116
							(.053)	(.060)*
% employment							1.218	5.104
							(2.170)	(2.506)**
% vacant								.460
								(1.868)
% owner-occupied								3.998
								(1.130)***
% houses w/ mortgage								-1.568
								(1.284)
median rent								1.141
								(.592)*
median house value								.044
								(.003)***
Observations	454692	454692	377955	353188	353122	353122	333941	281883
R-squared	.094	.094	.101	.1	.111	.111	.116	.119
F-Stat	23300.12	15683.21	10582.17	6510.449	2732.265	2575.023	1240.019	942.784

Note: The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Dependent variable is measured in 000s USD. County-level fixed effects included. For brevity, many coefficients are suppressed. "Education" includes percent of population with educational attainment of high school diploma or greater. "Marital status" includes percent of population nonmarried, widowed, or divorced. "Income" includes percent of population divided into 16 income brackets. Full results are available in the appendix.

Table 8: Instrumental variables regressions

credit limit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
util $	5.429	5.236	5.223	5.077	2.610	2.148	2.170	1.592
	(.354)***	(.324)***	(.352)***	(.478)***	(.367)***	(.604)***	(.611)***	(1.507)
% Black	3.487	68.742	71.427	70.124	37.947	32.941	33.117	25.699
	(1.575)**	(5.303)***	(5.936)***	(6.641)***	(4.888)***	(7.027)***	(7.119)***	(17.940)
score	.116	.130	.133	.132	.109	.103	.104	.098
	(.003)***	(.004)***	(.004)***	(.005)***	(.003)***	(.005)***	(.005)***	(.013)***
score * % Black		-.107	-.113	-.110	-.060	-.050	-.050	-.038
		(.007)***	(.008)***	(.010)***	(.008)***	(.012)***	(.012)***	(.029)
age			.143	.142	.118	.116	.117	.110
			(.010)***	(.010)***	(.006)***	(.008)***	(.008)***	(.015)***
violent crime			-305.652	-333.645	-425.323	-362.237	-353.119	-560.986
			(679.717)	(669.331)	(466.236)	(448.922)	(447.087)	(386.289)
property crime			94.066	101.629	141.640	142.102	143.461	182.785
			(111.262)	(108.624)	(69.966)**	(73.179)*	(72.843)**	(59.780)***
education				included	included	included	included	included
marital status				included	included	included	included	included
foreign-born				included	included	included	included	included
income					included	included	included	included
public assistance					included	included	included	included
inc growth (inflation adj)					.133	.147	.147	.131
					(.076)*	(.097)	(.097)	(.101)
% employment					-2.040	2.088	2.352	3.252
					(2.684)	(3.084)	(3.090)	(3.754)
% vacant						-1.785	-1.441	-1.081
						(2.695)	(2.685)	(2.881)
% owner-occupied						3.498	3.692	3.467
						(1.334)***	(1.328)***	(1.275)***
% houses w/ mortgage						-1.266	-1.254	-1.674
						(1.391)	(1.383)	(1.377)
median rent						.486	.441	.722
						(.812)	(.811)	(.820)
median house value						.022	.021	.029
						(.011)*	(.011)*	(.020)
Observations	334250	334250	276942	276892	260517	219421	220483	239114
R-squared	-.692	-.574	-.608	-.524	.33	.381	.379	.381
F-Stat	780.025	628.446	389.536	215.027	278.231	305.401	300.724	367.882
e(Hansen J-stat)	6.791	4.24	5.379	8.275	.049	.199	n/a	n/a
e(p-value)	.009	.039	.02	.004	.824	.655	n/a	n/a
e(Kleibergen-Paap LM-stat)	20.342	21.771	19.582	17.866	17.043	13.877	11.93	2.412
e(p-value)	.00004	.00002	.00006	.0001	.0002	.001	.0006	.12
e(Kleibergen-Paap F-stat)	802.641	853.618	783.892	239.979	54.592	22.404	42.977	8.203

Note: The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. County-level fixed effects included, and standard errors are robust to heteroskedasticity and clustered at the county level. Columns 1-6 include average neighboring wealth for the relatively richer within 1-4 miles and 4-20 miles as instruments. Column 7 uses only the 1–4-mile radius instrument while column 8 uses only the 4–20-mile radius instrument. Dependent variable and util $ are measured in 000s USD. "Education" includes percent of population with educational attainment of high school diploma or greater. "Marital status" includes percent of population nonmarried, widowed, or divorced. "Income" includes percent of population divided into 16 income brackets. Refer to Table 3 for description of instruments. Full results are available in the appendix.

Table 9: First-stage IV regressions

util $

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Black	-1.111	-11.797	-12.694	-11.796	-12.489	-12.015	-12.033	-12.020
	(.272)***	(.596)***	(.630)***	(.599)***	(.652)***	(.733)***	(.731)***	(.700)***
score	-.006	-.009	-.009	-.009	-.009	-.008	-.008	-.008
	(.0003)***	(.0004)***	(.0004)***	(.0004)***	(.0004)***	(.0004)***	(.0004)***	(.0004)***
score * % Black		.017	.019	.020	.020	.019	.019	.019
		(.0008)***	(.0008)***	(.0009)***	(.0009)***	(.001)***	(.001)***	(.001)***
age			-.009	-.009	-.008	-.009	-.009	-.010
			(.003)***	(.003)***	(.003)***	(.003)***	(.003)***	(.003)***
violent crime			-110.708	-93.703	-115.376	-19.824	-8.682	-72.248
			(141.067)	(144.139)	(145.739)	(162.694)	(162.563)	(135.044)
property crime			10.246	5.581	6.608	.677	1.334	7.278
			(25.914)	(26.314)	(26.350)	(31.433)	(31.259)	(24.117)
education				included	included	included	included	included
marital status				included	included	included	included	included
foreign-born				included	included	included	included	included
income					included	included	included	included
public assistance					included	included	included	included
inc growth (inflation adj)					-.022	.008	.009	.019
					(.023)	(.027)	(.026)	(.026)
% employment					2.957	2.445	2.499	1.987
					(.907)***	(.985)**	(.953)***	(.915)**
% vacant						.717	.653	1.138
						(.833)	(.816)	(.789)
% owner-occupied						.344	.373	.265
						(.526)	(.512)	(.495)
% houses w/ mortgage						.122	.138	-.157
						(.487)	(.486)	(.444)
median rent						.028	.025	.105
						(.283)	(.287)	(.267)
median house value						.009	.010	.011
						(.003)***	(.003)***	(.003)***
GTaggine 1-4 miles	.042	.040	.051	.064	.059	.047	.047	
	(.010)***	(.010)***	(.011)***	(.012)***	(.012)***	(.012)***	(.012)***	
GTaggine 4-20 miles	.081	.088	.089	.044	.013	.005		.029
	(.011)***	(.011)***	(.012)***	(.013)***	(.018)	(.019)		(.017)*
Observations	334250	334250	276942	276892	260517	219421	220483	239114
R-squared	.008	.009	.01	.011	.011	.012	.012	.012
F-Stat	145.241	165.397	101.823	64.681	39.029	30.985	31.76	33.663

Note: The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. County-level fixed effects included, and standard errors are robust to heteroskedasticity and clustered at the county level. Dependent variable is measured in 000s USD. For brevity, many coeficients are suppressed. "Education" includes percent of population with educational attainment of high school diploma or greater. "Marital status" includes percent of population nonmarried, widowed, or divorced. "Income and employment" includes percent of population divided into 16 income brackets, as well as the percentage of population receiving public assistance, with earnings, and the inflation-adjusted income growth. Full results are available in the appendix.

Table 10: Interaction of age with race

credit limit	(1)	(2)	(3)
util $	2.148	2.148	2.058
	(.604)***	(.604)***	(.621)***
% Black	32.941	33.275	73.045
	(7.027)***	(7.952)***	(7.016)***
score	.103	.103	.102
	(.005)***	(.005)***	(.005)***
score * % Black	-.050	-.049	-.045
	(.012)***	(.011)***	(.012)***
age	.116	.117	2.090
	(.008)***	(.011)***	(.423)***
age^2			-.019
			(.004)***
age * % Black		-.010	-1.807
		(.035)	(.183)***
age^2 * % Black			.017
			(.002)***
inc growth (inflation adj)	.147	.147	.124
	(.097)	(.097)	(.097)
% owner-occupied	3.498	3.501	3.447
	(1.334)***	(1.334)***	(1.334)***
% houses w/ mortgage	-1.266	-1.276	-1.342
	(1.391)	(1.393)	(1.377)
median house value	.022	.022	.022
	(.011)*	(.011)*	(.011)**
crime	included	included	included
education	included	included	included
marital status	included	included	included
foreign-born	included	included	included
income	included	included	included
public assistance	included	included	included
% employment	included	included	included
% vacant	included	included	included
median rent	included	included	included
Observations	219421	219421	219421
R-squared	.381	.381	.397
F-Stat	305.401	299.025	296.46
e(Hansen J-stat)	.199	.198	.135
e(p-value)	.655	.656	.714
e(Kleibergen-Paap LM-stat)	13.877	13.897	13.347
e(p-value)	.001	.001	.001
e(Kleibergen-Paap F-stat)	22.404	22.43	21.439

Note: The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. Results are based on IV regression specification as in Table 8. County-level fixed effects included, and standard errors are robust to heteroskedasticity and clustered at the county level. Dependent variable and util $ are measured in 000s USD. For brevity, many coefficients are suppressed. "Education" includes percent of population with educational attainment of high school diploma or greater. "Marital status" includes percent of population nonmarried, widowed, or divorced. "Income" includes percent of population divided into 16 income brackets. Full results are available in the appendix.

Table 11: Payday lending

credit limit	(1)	(2)	(3)	(4)	(5)
util $	2.148	2.131	2.126	2.154	2.154
	(.604)***	(.605)***	(.604)***	(.608)***	(.610)***
% Black	32.941	32.766	31.745	31.422	31.288
	(7.027)***	(7.022)***	(7.167)***	(6.787)***	(7.117)***
score	.103	.103	.103	.108	.108
	(.005)***	(.005)***	(.005)***	(.006)***	(.006)***
score * % Black	-.050	-.049	-.049	-.047	-.047
	(.012)***	(.012)***	(.012)***	(.011)***	(.011)***
age	.116	.116	.116	.117	.117
	(.008)***	(.008)***	(.008)***	(.008)***	(.008)***
inc growth (inflation adj)	.147	.147	.149	.148	.148
	(.097)	(.098)	(.099)	(.099)	(.099)
% owner-occupied	3.498	3.387	3.369	3.475	3.472
	(1.334)***	(1.332)**	(1.330)**	(1.323)***	(1.323)***
% houses w/ mortgage	-1.266	-1.338	-1.375	-1.535	-1.539
	(1.391)	(1.383)	(1.381)	(1.393)	(1.391)
median house value	.022	.021	.021	.021	.021
	(.011)*	(.011)*	(.011)*	(.011)*	(.011)*
PD-3mile		-.026	-.040	.387	.384
		(.018)	(.023)*	(.102)***	(.109)***
PD-3mile * % Black			.103		.014
			(.067)		(.071)
PD-3mile * score				-.0007	-.0007
				(.0002)***	(.0002)***
crime	included	included	included	included	included
education	included	included	included	included	included
marital status	included	included	included	included	included
foreign-born	included	included	included	included	included
income	included	included	included	included	included
public assistance	included	included	included	included	included
% employment	included	included	included	included	included
% vacant	included	included	included	included	included
median rent	included	included	included	included	included
Observations	219421	219421	219421	219421	219421
R-squared	.381	.381	.382	.381	.381
F-Stat	305.401	298.509	303.613	326.789	330.797
e(Hansen J-stat)	.199	.17	.174	.167	.167
e(p-value)	.655	.68	.677	.683	.682
e(Kleibergen-Paap LM-stat)	13.877	13.794	13.703	13.854	13.701
e(p-value)	.001	.001	.001	.001	.001
e(Kleibergen-Paap F-stat)	22.404	22.075	21.989	21.764	21.594

Note: The symbols *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively. County-level fixed effects included, and standard errors are robust to heteroskedasticity and clustered at the county level. Instruments as in Table 8. Dependent variable and util $ are measured in 000s USD. For brevity, many coefficients are suppressed. "Education" includes percent of population with educational attainment of high school diploma or greater. "Marital status" includes percent of population nonmarried, widowed, or divorced. "Income" includes percent of population divided into 16 income brackets. Full results are available in the appendix.