Credit Scores, Race, and the Life Cycle of Credit: Evidence from Credit Records

Robert B. Avery, Kenneth P. Brevoort, and Glenn Canner
Board of Governors of the Federal Reserve System
Washington DC 20551

September 22, 2008

Preliminary Draft
Do not cite or distribute with permission

Views stated are those of the authors and not necessarily those of the Board of Governors of the Federal Reserve System or its Staff. We thank Sean Wallace and Rebecca Tsang for tireless research assistance and Dan Sokolov, Leonard Chanin, Gregg Forte, Brian Bucks, Karen Pence, Myron Kwast, Chet Wiermanski, Frederic Huynh, Jesse Leary, and Matias Barenstein for helpful comments and suggestions.

I. Introduction

An extensive literature exists on racial differences in the access to and pricing of mortgage and consumer credit. With strikingly few exceptions, this literature documents differences in lending outcomes (for example, in the disposition of loan applications or loan prices) without attempting to isolate the root causes for these differences or to examine how differences in credit outcomes are affected by the interplay of other economic or social factors.

One of the main factors that affect observed outcomes in consumer credit markets is an applicant's (or borrower's) creditworthiness. While creditworthiness is important, it is also hard to measure. Some factors that affect an individual's creditworthiness can be relatively easily quantified and used by a lender (such as income), but other factors (perhaps related to the degree of financial literacy or character of the borrower) are harder to ascertain accurately in a manner that can be easily incorporated in evaluating loan applications. For this reason, lenders generally rely on generic "credit (history) scores" (sometimes referred to as bureau scores) as proxies for borrower creditworthiness. Generic credit scores, such as the well-known FICO scores, are statistically derived from information on an individual's past credit usage and performance, as reflected in the files of credit reporting agencies.

Despite the widespread use of credit scoring (including in non-credit areas such as insurance and employment), no study has assessed the extent to which credit scores accurately measure the creditworthiness of individuals of different racial or ethnic groups. The primary reason is the difficulty of assembling appropriate data. Data sources that rely on self-reported interviews, such as the Survey of Income Program Participation (SIPP) or the Survey of Consumer Finances (SCF), which contain detailed data on credit outcomes, race, and demographics, are not fully appropriate as most individuals are not fully aware of their own credit scores. Similarly, data sources drawn from loan applications or credit reporting agency files, which do contain information on credit scores and credit outcomes, are also insufficient as they generally lack information on race and other demographic characteristics. This lack of information is partly a result of federal laws that prohibit the collection of racial data as part of a non-mortgage credit application outside of limited self-testing purposes. Consequently, most studies utilizing application-based data have been restricted to using proxies for race (such as the racial composition of the individual's neighborhood) in their analysis.

This paper fills this gap through the use of a unique dataset that was assembled by the Federal Reserve Board for a study mandated by Congress as part of the Fair and Accurate Credit Transactions Act of 2003. As a consequence of this congressional directive, the Federal Reserve was able to combine a nationally representative sample of 300,000 individual credit records observed at two periods of time (June 2003 and December 2004) from one of the three national credit bureaus with information from the records maintained by the Social Security Administration on the race and other personal demographic characteristics of each individual in the sample. Additional data was acquired from a large demographic information company on the marital status and other demographic characteristics of each individual in the sample. This unique dataset allows us to address for the first time several questions about the relationship between credit scores, credit performance, race, and other personal demographic characteristics.

Specifically, in this study we examine three issues that existing research has been unable to address. First, we examine how credit scores differ across racial or ethnic groups for a nationally representative sample of individuals. We find substantial differences in credit scores across racial groups, with blacks and Hispanic whites having notably lower credit scores than other racial groups. These racial differences persist, even after controlling for other demographic characteristics such as age, martial status, and an estimate of income.

Second, we examine the extent to which credit scores rank order the credit risk of individuals by comparing credit scores as of June 2003 with credit performance in the subsequent 18 months. We also examine the extent to which credit scores are predictive of future payment performance for different racial and ethnic groups.

Concerns have been raised about the predictiveness of credit scores for minority groups which disproportionately use non-traditional sources of credit (for example, payday lenders and pawn shops) that do not report information to credit bureaus. Consequently, the credit records of such populations may contain less information about past and current borrowing patterns and, as a result, may be less accurate predictors of future credit risk or may lead to artificially low credit scores for minorities. Our analysis finds that credit scores in June 2003 successfully rank ordered credit risk, in that the observed delinquency rates declined as credit scores increased. This rank ordering held for the population as a whole and for each racial or ethnic group examined. Furthermore, we find that blacks and Hispanic whites tend to perform worse on their credit obligations than white borrowers with similar credit scores. These differences are reduced, but not eliminated, when other personal demographic or neighborhood characteristics are controlled for. This result suggests that the credit scores for black and Hispanic white borrowers tend to be higher than their subsequent credit performance would warrant. To shed more light on these observed relationships, this study examines why certain groups have lower credit scores by examining the "lifecycle of credit."

The remainder of this paper is organized as follows. In the next section we provide general background and lay out a framework for the analysis. The following section describes the specific data and methodology used in our analysis. We examine the relationship between race, credit worthiness and loan performance in the next section, followed by an examination of racial and ethnic differences in the lifecycle of credit. Issues of credit access and loan pricing are addressed in the next section followed by conclusions and qualifications. .

II. Background

Previous Research on Race and Credit.

As stated above, there is virtually no empirical literature which examines the interplay between race or ethnicity, outcomes in the credit market (specifically, the disposition of loan applications, loan prices and loan performance), and creditworthiness. A number of studies have examined part of this relationship. For example, studies of annual data released pursuant to the Home Mortgage Disclosure Act (HMDA) consistently show that blacks and Hispanics have higher denial rates and have higher mortgage borrowing costs, on average, than non-Hispanic whites in the same markets with similar incomeS, loan sizes, and lenders (see Avery, Canner and Cook (2005) and Avery, Brevoort and Canner (2006, 2007, and 2008). Unfortunately, these studies contain no information on loan performance and little on the creditworthiness of the loan applicant other than income and loan size. They also lack information on the specific underwriting standards employed by different lenders. A study of 1990 HMDA data suggested that racial and ethnic differences in denial rates can be narrowed but not eliminated when a range of creditworthiness factors collected in a supplemental survey are controlled for (Munnell e. al. 1996). Zorn (xxxx) reached a similar conclusion regarding mortgage pricing. Neither of these studies contained any information on loan performance.

Research by Berkovec, Canner, Hannan and Gabriel (1996) and Reeder (1999) are the only public studies we are aware of which relate race or ethnicity, loan performance and creditworthiness in mortgage lending. Both studies are based on special datasets containing mortgage performance information for FHA loans. Berkovec et al. found that black borrowers showed higher delinquencies and defaults than non-Hispanic whites with comparable creditworthiness measures and loan pricing at the time of loan origination. Reeder found a more complicated relationship with black borrowers with high ex-ante measures of creditworthiness underperforming and those with low ex-ante creditworthiness overperforming.

These studies have focused on mortgage credit partly because datasets with both credit market outcomes and racial and ethnic information are available in HMDA data or FHA loan records. Studies of racial and ethnic differences in outcomes in other credit markets, such as credit cards and auto loans, have been limited to indirect inferences comparing debt holdings in surveys such as the SCF (see Kennickel and Bucks and Edelberg). Like research based on HMDA data, these studies lack good measures of creditworthiness and little information on loan performance.

One of the few studies of race and non-mortgage loan performance was conducted by Fair Isaacs (xxxx) using the racial and ethnic composition of an individual's zip code as a measure of race. The analysis used a nationally representative sample of roughly 800,000 credit records of individuals. The analysis revealed that the share of individuals from high minority areas with relatively low credit scores was about twice as large as the share of individuals from other areas. This research further found that for the high minority area and other populations, credit scores performed well in rank-ordering future loan performance. The analysis concluded that Fair Isaac credit scores are both effective and "fair" in assessing risk for both populations.

Empirical Framework

The approach taken here is similar to that employed by Berkovec et al. We use a nationally representative panel of individuals drawn from credit record files as of June 2003 and updated as of December 31, 2004. The individuals in the sample were matched to Social Security datafiles to obtain information on race and other personal demographic characteristics and to Census Bureau files to obtain information on their neighborhood (census block or, if block was not known, census tract,) economic and demographic characteristics. The census match is used primarily to obtain a crude, location-based estimate of the individual's income because income is not included in credit record data.

The individual's creditworthiness is assessed by matching two commercially-available credit scores constructed from June 2003 credit bureau data to the datafile. Finally, loan performance is estimated for each individual by comparing credit account-level measures of performance measured at June 2003 and December 2004. Bad performance is defined as an account which was in good standing in June 2003 and become seriously delinquent or defaulted by December 2004. Credit access and pricing is estimated by determining which individuals obtained new credit between June 2003 and December 2004 and at what interest rate.

Given this dataset, we explore the interplay between race, creditworthiness, loan performance and credit access in the following way. We first examine racial and ethnic differences in credit worthiness (as measured by the credit scores) and determine the extent to which such differences can be explained by differences in other demographics, income, and neighborhood. We pay particular attention to life-cycle variables in this examination, quantifying how score differences vary with age and marital status.

The second phase of the analysis focuses on racial and ethnic differences in loan performance conditioned on creditworthiness and again how such differences can be explained by other personal demographics, income, and neighborhood location. The lifecycle implications of the two phases of the analysis are compared for logical consistency. The major factor used to the construction of credit scores is past loan performance. All else equal, individuals who underperform relative to others with the same credit score will tend to see their scores fall over time; those who overperform will see their scores rise. Thus, an implication of credit score differences between two groups that widens with age is either that the group with the higher mean scores is overperforming relative to their scores or that the group with the lower mean score is underperforming or both.

The final portion of the analysis focuses on issues of loan access. In particular, we examine whether conditioned on creditworthiness, there are differences in loan denials and loan pricing between racial and ethnic groups. Such differences would be possible indications of discrimination and, if so, might at least partially explain differences in loan performance.

III. Data Used for this Study

The data used for this study were drawn from five sources; (1) the complete credit records of a nationally representative sample of individuals as of June 2003 and again, for the same individuals, as of December 2004; (2) two commercially available measures of creditworthiness (credit scores) for each individual in the sample of credit records; (3) the race, ethnicity, sex, place and date of birth for each individual in the sample of credit records from a match to Social Security records; (4) the demographic and economic characteristics of the block groups or census tracts of the place of residence of each individual in the credit record sample from the 2000 decennial census; and (5) a file of mean credit scores by census tract for the US population as of December 2004. We describe these data and our use of them in more detail as follows.

The Sample of Credit Records

We obtained from TransUnion, one of three national credit reporting agencies, the full credit records (excluding any identifying personal or creditor information) of a nationally representative random sample of 301,536 individuals as of June 30, 2003.[1] We subsequently received updated information on the credit records of these individuals as of December 31, 2004. Some individuals (15,743) in the initial 2003 sample no longer had active credit records as of December 31, 2004, in some instances because the individual had died. However, other factors may also have limited the ability to update records. A total of 285,793 individuals still had active credit files as of December 31, 2004.

[1] The credit reporting industry is dominated by three national credit reporting agencies -- Equifax, Experian, and TransUnion. These firms seek to collect comprehensive information on all lending to individuals in the United States and have records on perhaps as many as 1.5 billion credit accounts held by approximately 225 million individuals. Together, the three national agencies generate more than 1 billion credit reports each year. The vast majority of these reports are provided to creditors, employers, and insurers.

The credit record data contain all of the information typically needed to assess the generic creditworthiness of an individual from the perspective of their past experience with credit. The credit account-level data fall into five broad categories: account identification (e.g. single or joint), account dates (date opened, closed or transferred), account balances (current and highest ever), account description (type of lender and loan, for example, home mortgage or credit card), and payment performance. Payment performance data include the extent of current and historical payment delinquencies extending back 48 months, as well as information on other account derogatories. Payment delinquency information is recorded in four classes of increasing severity — 30 to 59 days; 60 to 89 days; 90 to 119 days; and 120 or more days past due, charged off , in collection, or those associated with a judgment, bankruptcy, foreclosure or repossession. Typically, accounts that are 120 or more days past due and accounts with other derogatories are grouped together and termed "major derogatories."

In addition to credit account information, the credit record data include information derived from monetary-related public records and reports from collection agencies, including information on non-credit-related bills, most commonly bills for medical or utility services. Finally, limited information on credit inquiries from prospective lenders is also included in the credit record files.

Credit record data can be used to construct measures of loan performance. Most performance measures developed by industry model builders are constructed by looking backwards from the date the credit report was pulled. For most credit accounts, historical information on the payment performance for the preceding 48 months is given. For these accounts, the information is sufficient to assess performance over any performance period within those 48 months. Similarly, filing dates for collection and public records determine the precise date when such events occurred. However, month-by-month payment records are not available for all accounts, particularly those that are seriously delinquent. For these accounts, the only information available is the date of last delinquency; it is not possible to determine if it was also delinquent in the months preceding that point. Because of the inability to determine how often an account has been delinquent for all accounts, or when it first became delinquent, performance is typically determined by whether *any* of the individual's accounts suffered *any* of a specific group of payment problems during a performance period. Generally the performance window is the 18- or 24- month period preceding the date of the credit report. Typically the industry defines bad performance as accounts that became 90 or more days delinquent or were in foreclosure or collection, or were otherwise in serious distress or loss during this period.

One of the objectives of this study is to link measures of creditworthiness with loan performance over a subsequent period. Here, we take advantage of the fact that we have two data snapshots drawn for the same individuals. We measure creditworthiness as of the first date and measure loan performance looking back over the 18-month period between the two draws using information solely contained in the second data draw. Two performance measures are constructed. The “any account” measure is based on performance on new (opened between July 2003 and December 2003) or existing (opened June 2003 or before and not closed before July 2003) accounts and measures whether an individual has been 90 or more days late on one or more of their accounts had a public record item or a new collection agency account during the performance period. This is a measure commonly used by the industry.

As noted, the precise time when a credit account became bad often cannot be determined. Consequently, rules are developed to implement somewhat arbitrary decisions about how to determine whether an account was bad before the beginning of the performance period or whether it went bad subsequently. Errors in those decisions can create a spurious correlation between the performance measure and measures of creditworthiness at the beginning of the performance period. Consequently, industry developers of credit risk models generally validate their models using only unambiguously out-of-sample performance measures, such as accounts that are known to have been opened after the beginning of the performance period.

To address the concern that a seemingly new account in the present database may have actually existed and gone bad before the opening of the performance period, an additional measure of performance, called the “new-account” measure was constructed from the credit records. However, unlike the any account measure which included all accounts opened after the beginning of the performance window (July 2003), some new accounts were eliminated from this performance measure if they appeared to have a high propensity to be reported only when performance is bad. The accounts excluded consisted of student loans and utility, medical, and factoring accounts. Whenever any such account appears in the July 2003 to December 2003 window as new, it likely was already in existence but was not reported as opened until the later time. All these accounts were excluded regardless of their performance; doing so eliminated only about 10 percent of the new accounts but removed more than 50 percent of all the bad accounts. To better emulate industry out-of-sample performance measures, the new-account measure was computed at the account level rather than—as in the any account measure—at the person level. Bad performance is defined as it is in the other performance measure (major derogatory or 90 or more days delinquent during the performance period).

The percentage of accounts that become bad varies greatly across the two performance measures. Twenty-eight percent of individuals in the sample exhibited bad performance using the any-account measure, compared to only 3.4 percent using the new accounts measure.

Assessing Creditworthiness

There are many different measures of creditworthiness. Since the 1960's there has been an increased use of statistically-derived credit scoring models which evaluate credit risk mechanically. The inputs needed to form risk predictions from these models are typically variables constructed from information in an individual's credit records as well as information supplied on a credit application. There are now literally thousands of such models and few consumers would receive a mortgage or other consumer credit without the aid of a prediction from a credit scoring model.

For this study we focus on credit scoring models as our measure of creditworthiness and further restrict the class of such models to the set of models where the factors used to form the prediction are restricted to the information included in the records maintained by credit reporting agencies. The predictions from such models are termed "credit history scores," and are typically numeric predictions with higher scores representing "better" predicted credit performance and lower scores worse performance. When the population used in model development is based on a representative sample of all individuals in credit reporting agency records and the measure of performance is based on any type of credit account, the resulting model is typically referred to as a *generic* credit history scoring model.

Several different outcome measures are used in the development of the generic credit history scoring models widely used today, but most reflect some form of generic credit performance (for example, delinquency on any new or existing credit account).

Although the lending industry and firms that support their activities have developed a great many versions of a generic credit history score, the first, and still the mostly commonly used such score is the FICO score developed by Fair Isaac and Company (Fair Isaac). The FICO score, like most other generic credit scores, rank-orders consumers by the likelihood they will become seriously delinquent on any credit account in the near future (typically over the next 18 to 24 months).[2] In addition to the FICO score, the three national credit reporting agencies have developed and make available their own generic proprietary credit history scores. These credit history scores may differ in terms of the type of delinquency they are predicting. For example, some scores may predict the likelihood of delinquency among existing accounts and others may focus on delinquency among new accounts. Recently, the three national credit reporting agencies jointly developed and are now marketing a new generic credit history score named the VantageScore.[3]

For this study, TransUnion provided two different generic credit history scores for each individual in the sample—the TransRisk Account Management Score (TransRisk Score) and the VantageScore.[4] The two scores used here are as of the date the sample was drawn. The TransRisk Score was generated by TransUnion's proprietary model for assessing the credit risk of existing accounts. In particular, the TransRisk Score was constructed with a selected group of factors drawn from the credit records of individuals to predict the

[2] The characteristics created for developing a generic credit history model tend to be similar across different models. These characteristics generally fall into five broad areas: payment history, consumer indebtedness, length of credit history, types of credit used and the acquisition of new credit. The characteristics that fall into these five areas are not all of equal importance in determining credit scores. For example, for the general population, Fair Isaac reports that payment history characteristics are the most important category accounting for about 35 percent of their score's predictiveness; consumer indebtedness 30 percent; length of credit history 15 percent; and, types of credit used and acquisition of new credit each adding about 10 percent. For particular subpopulations, such as those with only a short history of credit use, these categories may differ some from the general population in importance. Refer to www.myfico.com.

[3] The VantageScore was developed jointly by Equifax, Experian, and TransUnion to create a measure of credit risk that scores individuals consistently across all three companies. The model was developed from a national sample of approximately 15 million anonymous credit files of individuals drawn from each of the agencies credit files. The performance period used to estimate the model was June 2003 to June 2005.

[4] We also used a third score; a score we developed with the available data emulating the process followed by industry generic credit history score modelers. Results from this Federal Reserve model are not fundamentally different from results using the two commercially available scores and are thus not presented here.

likelihood that at least one existing credit account would become seriously delinquent over an ensuing performance period. The VantageScore predicts the likelihood that a random credit account of an individual will become seriously delinquent over the performance period.

TransUnion also supplied a file of the mean TransRisk Scores by census tract for individuals both with and without a mortgage. The means were based on a nationally representative sample of about 27 million individuals drawn from all credit records maintained by TransUnion as of December 31, 2004. The database was used to determine the overall mean score for individuals in the census tract as a weighted average of the mean scores of those with mortgages and those without.

Comparing credit scores derived from different credit-scoring models requires "normalizing" the scores to a common scale. However, no natural, universal normalization formula exists. Because the particular normalizations used for the TransRisk Score and VantageScore are unknown, it was decided to renormalize each of the scores used in this study to a common rank-order scale. The normalization was based on the 232,467 individuals in our sample for whom both credit scores were available as of June 2003. Individuals were ranked by the raw values of each of the two credit scores as of June 2003, with a higher rank representing better performance. Individuals at the 5 percent cumulative distribution level for each credit score were assigned a score of 5; those at the 10 percent level were assigned a score of 10; and so on, up to 100 percent. Linear interpolations were used to assign credit scores within each 5 point interval to ensure the functional form was smooth. The census-tract mean TransRisk Scores were normalized using the same normalization as the individuals in the sample.

Under this method of normalizing, each individual's rank in the population is defined by his or her credit score: For example, a score of 50 places that individual at the median of the distribution, and a positive change of 5 points in an individual's credit score means that individual moves up 5 percentage points in the distribution of credit scores. Because each score is normalized in exactly the same way, comparisons of the overall distributions across the different scores are not meaningful. However, the normalization facilitates comparisons across different populations for each of the scores.

Locational Information from Census 2000 Data.

At the request of the Federal Reserve, TransUnion "geocoded" the current address of each individual in the sample to help identify the year 2000 census block group of the person's residence.[5] The census block location of about 15 percent of the sample could not be identified, and for an additional very small number of individuals in the sample (544), not even the census tract could be identified. This geographic information was matched to Census 2000 files at the U.S. Bureau of the Census; those data include the racial or ethnic makeup and income of each census block group as of April 2000. For the portion of the sample where block was missing, census tract data were used.

Demographic Information from the Social Security Administration.

Most of the demographic data used in this study were obtained from a match of individuals in the credit files to data maintained by the Social Security Administration (marital status was not available from the SSA so it was obtained from a match to a national demographic company). The SSA gathers demographic information on the form used by individuals to apply for a Social Security card.[6] The SSA data are the same items that are made available to other researchers and government agencies conducting studies that require personal demographic information.

With the names and Social Security numbers provided by TransUnion, the SSA extracted and provided to the Federal Reserve the following information for each matched individual to the extent available: citizenship, the date the individual filed for a Social Security card, place of birth, state or country of birth, race or ethnic description, sex, and date of birth.[7] All this information except the race or ethnicity of the applicant is required on the

[5] A census block group is a cluster of census blocks (up to nine) within the same census tract. Census blocks vary in size, often relatively small in urbanized areas, but much larger in rural areas. Census block groups generally contain between 600 and 3,000 individuals, with an optimum size of about 1,500. Census tracts typically include about 4,000 individuals (www.census.gov). No specific addresses of individuals in the sample of credit records used for this study were provided to the Federal Reserve.

[6] The application form for a Social Security card is SS-5 (05-2006) at www.ssa.gov/online/ss-5.html.

[7] The procedures followed for this study ensured that the SSA received no information included in the credit records of the individuals other than the personally identifying information needed to match the administrative records maintained by the SSA. The Federal Reserve received from the SSA a data file that included the demographic characteristics of the individuals in the sample but no personally identifying information. TransUnion did not receive any information from the SSA or the Federal Reserve on the demographic characteristics of the individuals in the sample.

application form for a Social Security card; race or ethnicity is requested on the form, but the applicant is not required to supply it.

Overall, almost 80 percent of the 301,536 individuals in the sample could be matched to SSA records. An even larger proportion, 90 percent of those with a credit score as of June 30, 2003 -- the sample most relevant for this analysis -- could be matched to SSA records. Age and sex were available for virtually all of the individuals matched to the SSA records. Information on race or ethnicity was available for almost 97 percent of the individuals matched to the SSA records.

Several issues had to be addressed before the SSA data could be used. First, about 51 percent of the sample individuals had more than one SSA filing, and the data in some of those cases was inconsistent. Second, the age data supplied by the SSA was sometimes implausible because it implied that the individual was extremely old or young or because it was inconsistent with the age of the individual's oldest account in their credit record.[8] Third, the question on race and ethnicity on the application form for a Social Security card changed in 1981. These issues were dealt with as follows.

In general, when individuals filed more than one application for a Social Security card, we used information from the most recent filing. Various rules were used to identify and address implausible values for age in the SSA data. An implausible age suggested that the SSA record and TransUnion records had potentially been mismatched, and in such cases all SSA data for demographic items—age, race, ethnicity, and sex—were treated as "missing." In total, only about 2 percent of the sample had ages deemed to be implausible.

The most difficult inconsistency in the SSA data came from the change in the options provided to individuals for identifying their race or ethnicity when applying for SSA cards. For the years preceding 1981, individuals had three choices, from which they were asked to select one—"White," "Black," or "Other." Beginning in 1981, individuals have had five options, from which they are asked to select one—(1) "Asian, Asian American, or Pacific Islander," (2) "Hispanic," (3) "Black (Not Hispanic)," (4) "North American Indian or Alaskan Native," and (5) "White (Not Hispanic)." To employ a single set of categories for

[8] To be included in the study sample, an individual must have had a credit record as of June 30, 2003. Individuals who were, for example, younger than 15 years of age are highly unlikely to have had credit records. Consequently, such an age for individuals with credit records likely represents a mismatch between the credit-reporting agency records and the SSA records.

race and ethnicity and retain the greater detail available after 1980, we chose to use the five post-1980 categories. The problem then focused on "pre-1981" individuals, those whose only application for a Social Security card was before 1981 (about 40 percent of the sample); their set of three responses would have to be distributed across the set of five responses available after 1980. We chose to address this issue by imputing whether a pre-1981 individual who chose white or black would have instead selected one of the three options unavailable before 1981 if they had had the opportunity to do so: Asian, Asian American, or Pacific Islander (hereafter, Asian); Hispanic; or North American Indian or Alaskan Native (hereafter, Native American). For those answering "other," the question is which of the five options, including white or black, they would have chosen since the option, other, would no longer have been available.

The "imputation" is the probability that an individual would select one of the missing options; the probability is calculated from a multinomial logistic model estimated with data from individuals applying for Social Security cards in the 1981-85 period. The imputation model was validated against the responses of individuals who filed applications for Social Security cards before 1981 and then filed again in 1981 or later.[9]

This procedure does not result in imputation of race for all pre-1981 sample individuals. With the exception of one small group, whose race was imputed to be black or white by the model, all of the pre-1981 individuals treated as black or non-Hispanic white in our analysis would have reported their race in corresponding terms to the SSA if they had applied for a Social Security card after 1980. The exception was a small number of pre-1981

[9] Specifically, the imputation process was conducted as follows. The estimation sample was divided into cells by age (two groups, over 30 years of age and 30 or younger), marital status, and sex. A set of dichotomous indicator variables was generated based on an individual's reported SSA race or ethnicity selection. White was the excluded category for the estimation. Each nonwhite SSA race choice was then regressed using a logistic model form on a combination of variables relevant to the race in question. These variables included each individual's ethnic background, foreign-born status, language preference and religion based on information supplied from the national demographic company (based mainly on a name match), a measure of the racial or ethnic composition in the individual's census block or census tract, and this measure of composition interacted with the individual's ethnicity and language preference. The variables involving racial and ethnic concentration were capped at .001 and .999 and then log-odds transformed. In cells for which logistic regression was impossible a linear probability model was used. These models were used to predict the racial or ethnic choice that would have been made by individuals whose only SSA application was prior to 1981. After all five probabilities were generated they were normalized so that they summed to 1.

Pre-1981 individuals classifying themselves as white were assigned a zero probability of being black; the model coefficients were used to assign one of the other four choices for the individual. A similar rule was applied for pre-1981 individuals classifying themselves as black—that is, they were assigned a zero probability of being white—and in addition they were assigned a zero probability of being Native American. No restrictions were imposed for pre-1981 individuals classifying themselves as "other."

individuals who classified themselves as "other" and were not assigned high probabilities of being Hispanic, Native American or Asian. The major impact of the procedure is on the Asian, Hispanic, and Native American groups, whose entire pre-1981 portion of the sample had to be "carved out" from the pre-1981 white, black, and "other" groups.

Basic Sample Statistics

In total, there are 301,536 individuals in the study sample. These individuals are separated into two groups for most of the analysis. The primary group is the 232,467 individuals with both a TransRisk Score and a VantageScore (table 1). This is the base sample used to evaluate credit score and performance differences across populations. The other group is the 69,069 remaining individuals lacking at least one score that were not used for most of the analysis.[10]

Most of the analysis uses individual race as defined in the SSA data. However, we also redo most of the analysis using a racial and ethnic definition based on the racial and ethnic composition of the census block where the individual lives and present that in a separate section.[11] For both of these categories, there is an "unknown" group where race or ethnicity could not be determined. For each racial and ethnic grouping, summary statistics are presented that show the incidence of selected items in credit record records for the two sample populations (table 1). Not surprisingly, individuals in the full sample of credit records provided by TransUnion differ some from the records of individuals that could be scored. The principal difference is in the mean number of credit accounts for individuals, which is much lower for the full sample than for the scoreable sample.

The content of credit records differs greatly across racial and ethnic groups. For example, blacks are less likely than other racial or ethnic groups to have a revolving or

---

[10] Nineteen individuals in the sample were missing the TransRisk Score but were assigned a VantageScore; 17,533 were missing the VantageScore but had a TransRisk Score; 51,517 were missing both credit scores.

[11] As noted, racial or ethnic identity is not available in the data used to develop credit scores based solely on credit records. Consequently, the locational approach has been used in previous studies that examine the relationship between credit scores and race or ethnicity. In the locational approach, the adult racial or ethnic composition of the individual's census block (available for about 85 percent of the individuals) or census tract is used as an approximation of the individual's race or ethnicity. The proportion of the block belonging to each racial or ethnic group can be viewed as the probability that a random adult drawn from the block will have that race or ethnicity. The probability is used as a weight in forming the tables presented in this section and for analytic work presented later.

mortgage account and much more likely to have either a public record, or a reported medical or other collection item. Also, compared to other populations, blacks and Hispanics evidence elevated rates of at least one account 90 days or more past due.

As noted, the sample of credit records of individuals obtained for this study was nationally representative of the individuals included in the credit records of the national credit-reporting agencies.[12] Further comparisons were made to evaluate how closely the sample mirrors the population of U.S. adults (those aged 18 or more). The distribution of individuals in the sample population arrayed by their state of residence is quite similar to the distribution of all adults (individuals 18 or more) in the U.S. as of June 2003 as estimated by the Bureau of the Census (data not shown). Most importantly, the racial or ethnic characteristics of the sample population as assigned here closely mirror the distribution of race and ethnicity for all adults in the U.S. as reflected in the census, although the proportion of Hispanics in the sample population is somewhat lower than in the population overall (table 2). Here we show two different representations of the sample data. The data further show that the distribution by race and age of scoreable individuals differs from the distribution of individuals for whom scores were not available. Blacks in particular were less likely to have been scored.

IV. Race, Credit scores and Loan Performance

The normalized credit scores used in this paper don't precisely correspond to score thresholds used by lenders to segment borrowers by risk grade. Roughly though, a score in the top 60 percent of the distribution (a 40 or more) would place the individual in the prime market (the best possible prices for a mortgage); a score from the low 20's to high 30's would place the individual in the near-prime market (mortgage interest rates 1 or 2 percentage points above those in the prime market) and a score below 20 would place the individual in the subprime market (an interest rate more than 2 or 3 percentage points above prime). Against this backdrop, differences in the distributions of credit scores among racial and ethnic groups are striking (table 3). The mean TransRisk Score for Asians is 54.8; for non-Hispanic whites, it is 54.0; for Hispanics, 38.2; and for blacks, 25.6. More than one-half

[12] The sample was drawn as a systemic sample where individuals were ordered by location.. The sampling rate was about 1 out of 657.

of all blacks have scores in the subprime range; less than one-quarter are in the prime range. On the other hand, less than one-fifth of non-Hispanic whites have scores in the subprime range and over 65 percent are prime.[13]

Are credit scores consistent with performance? When loan performance is plotted against score for each score and performance measure, the general shapes of the curves are similar across demographic groups (figure 1).[14] However, the performance curves are not identical. The curves for blacks are consistently above the curves for other groups; whereas the curves for Asians are typically below that of others. A performance curve that is uniformly above (below) means that that group consistently underperforms (overperforms), that is, performs worse (better) on their loans, on average, than would be predicted by the performance of individuals in the overall population with similar credit scores.

These differences are seen in mean performance residuals; that is, the average differences in performance of individuals in a particular group from the mean performance of the full population at the same score level. Consistently, across both credit scores and both performance measures, blacks show higher incidences of bad performance overall (table 4) than would be predicted by their credit scores (table 5). Similarly, Asians consistently perform better than would be predicted by their credit scores.[15]

The relative sizes of the performance residuals and mean performance levels by group demonstrate the power of credit scores to predict performance both within and between groups. The mean percent bad of blacks for the any account performance measure is 65.9 percent and for non-Hispanic whites it is 22.6—a difference of 43.3 percentage points. This difference shrinks to 6.6 percentage points *simply by accounting for score.* The difference in new account performance, 8.0 percentage points, shrinks to 3.0 percentage points when score is taken into account.

Collectively, this evidence is consistent with the view that scores predict equally well within different racial and ethnic groups and are powerful predictors of performance across

[13] These credit score patterns by race or ethnicity are consistent with those presented in an analysis of consumer perceptions of creditworthiness. Refer to Marsha Courchane, Adam Gailey, and Peter Zorn (2007), "Consumer Credit Literacy: What Price Perception," paper presented at Federal Reserve System Conference, *Financing Community Development: Learning from the Past, Looking to the Future,* Washington, March 29-30.

[14] Figures are only presented for the TransRisk Score as patterns for the VantageScore are similar.

[15] Prediction residuals for populations with extremely small sample sizes, such as the Native American group, and for those with unknown census tracts should be viewed with caution because the performance estimates have large standard errors.

groups.[16] The score and performance data also suggest likely changes over time. The score levels of groups that consistently underperform would be expected to deteriorate over time because payment performance is a significant factor in credit-scoring models. The deterioration would be particularly pronounced to the extent that new accounts without a performance history are in the credit records. Alternatively, groups that consistently overperform would be expected to experience an increase in credit scores over time as a result of their good performance. Thus, the relative scores and performance of blacks and Asians should not be surprising.

Life-cycle Effects Patterns in Score and Performance

The life cycle patterns of score by race implied by the data are shown in figure 2. Young individuals of all racial and ethnic groups enter the credit system with scores close to the national average (50). However, mean scores for all racial and ethnic groups quickly plunge. By age twenty-five the average score of non-Hispanic whites falls to 35; for blacks, the fall is significantly larger, all the way to 16--well in the subprime range. For Hispanics whites, the fall is to 27, between the other two racial and ethnic groups.

From age twenty-five onward, mean scores slowly rise for all groups over the age range, suggesting that individuals either learn the consequence of bad credit performance or creditors limit credit access to proven bad performers. The rate of score increase for blacks, however, is less steep than for the other racial and ethnic groups. Consequently by age seventy-five, the average black score has still not reached the national average of 50. The score gap between blacks and non-Hispanic whites slowly widens, from 19 points at age twenty-five to 28 points at age forty-five and remains at that level until age seventy-five. Similarly the gap between Hispanic whites and non-Hispanic whites rises from 9 points at age twenty-five to 14 points at age forty-five and remains more-or-less at that level for the rest of the age range.

[16] Another way of measuring predictiveness is the Kolmogorov-Smirnov (KS) statistic, which is the maximum difference, across all score values in the cumulative percentage distributions of goods and bads. When each population is weighted to the same score distribution, the TransRisk any account KS statistics for white non-Hispanics are 72.2, for blacks 67.3, for Hispanics 67.4 and for Asians 70.8. While the KS statistics describes the ability of the model to differentiate goods from bads at a single point, another statistic, the mean divergence statistic, compares how the score means of the goods and bads compare. Here, the TransRisk any account mean divergence statistics for white non-Hispanics is 44.6, for blacks, 33.7, for Hispanics 34.8 and for Asians 38.4.

These age-score relationships abstract from any cohort effects and do not reflect controls for other factors such as income or marital status or other personal demographics. The score patterns are broadly consistent, though, with age-related patterns in loan performance (figures 3a and 3b). Using the all-account performance measure the biggest gap in performance between blacks and non-Hispanic whites is at age nineteen, with the performance gap narrowing to about 6 or 7 points at age thirty, where it remains more or less constant throughout the remainder of the age range (figure 4). Similar patterns occur for the new account performance measure (data not shown).

Regression Results Explaining Score Differences

The results presented so far are univariate statistics. Some of the differences in credit scores by race or ethnicity could arise from differences in the distribution by age or marital status of the different racial or ethnic groups. Score (or performance) differences could also arise, at least in part, from differences in economic circumstances, including income and locational factors. This section presents the results of a regression analysis conducted to isolate the effects of race on credit score by controlling for other characteristics available in the dataset.

Independent variables for the analysis were selected from several sources. SSA data on age were used to construct linear splines with five knot points (under 30, 30-39, 40-49, 50-61, 62 plus) separately for five sex/marital status groups (single female, single male, married female, married male, unknown sex or marital status). Credit records generally do not include information about individuals' economic or financial circumstances, such as their income, wealth, and work-related experience, nor do the other databases against which the credit score sample was matched. Ideally, one would like to account for the effects of these other circumstances in explaining differences in credit scores across populations. The credit-record data do, however, include information on the location of residence. This information was used to construct a number of additional control variables, and the multivariate analysis was broadened to include these additional measures.

A proxy measure of income was developed from census information. The 2000 Decennial Census provides the distribution of income for each racial or ethnic group segmented in seven age categories for each census tract. These distributions allow a calculation of an estimated average income for each racial or ethnic group by age within each census tract. This variable was used as an estimate of the income for each individual in the sample (individuals missing race or ethnicity were assigned the mean for their age group in their census tract of residence.) The empirical estimation also included other location-based controls including the relative income of the census tract of residence and the mean TransRisk Score of the individual's census tract of residence.[17] Because the TransRisk Score was used as the dependent variable in the regression and to derive the mean score for each census tract, the equation using the mean census tract credit score can be interpreted as a "fixed-effects" model, that is, a model structured to fully account for all types of socioeconomic differences among census tracts.

Finally, in all regressions, dummy variables were included for each racial or ethnic group with non-Hispanic whites used as the base group. The sample used for the regressions excluded individuals with unknown age or census tract. This reduced the sample used for the estimation by 11 percent. The regressions were run only for the TransRisk Score since that was the only score available for the census tract means.

As shown in table 6, the gross difference between non-Hispanic whites and blacks for the TransRisk Score in the multivariate estimation sample was 28.3 credit score points. The difference between non-Hispanic whites and blacks declines to 22.8 points when marital status and age are accounted for; the difference falls to 18.7 points when census tract income and the estimated income of the individual are taken into account. Accounting for the mean census tract credit score causes the difference to fall further to 13.4 points. The gross difference in mean TransRisk Scores between Hispanics and non-Hispanic whites (15.7 points) falls relatively more than for blacks and non-Hispanic whites; after accounting for all factors only a 3.9 point differential remains unexplained.

Regression Results Explaining Performance Differences

As with score differences, some of the differences in performance residuals by race may be explainable by factors other than race. Consequently, a regression analysis similar to that undertaken to evaluate score differences was conducted for loan performance. All of the independent variables used for the score regressions were included as well as credit score and

[17] The mean TransRisk Scores by census tract were normalized in the same manner as the TransRisk Score for the sample individuals.

score squared. To allow for interactive effects the analysis was conducted separately for three score ranges—the lowest score quintile, the second lowest, and the top three quintiles combined. The dependent variable in all cases was the individual's performance residual (only individuals with performance could be used in the sample). Regressions were run separately for the any-account and new account performance measures and only using the TransRisk Score.

Unlike the case of the multivariate analysis of credit score distributions, controlling for other personal demographic and census tract factors appears to have only a modest effect on performance residuals across race (table 7). For example, the performance residual for the any-account performance measure for blacks has a 5.6 percent bad rate, which is only reduced to 4.7 percent when other factors are taken into account. Thus, the performance residuals appear to largely reflect the group characteristic itself (or other factors related to the group characteristic that were not included in the model) and not the confounding effect of other personal demographic or locational factors.

Finally, another possible explanation for performance differences may be that different populations use different types of credit, borrow from different types of lenders, and receive different loan terms even when they have similar credit scores. The account details in the credit records allow for a limited characterization of such differences. The evaluation could technically be done for both existing credit accounts and for new accounts. The drawback to using existing accounts is that such accounts were taken out at different times preceding the draw of sample of credit records and thus may not reflect an individual's current credit circumstances. On the other hand, by focusing on new accounts, the credit score of June 2003 more credibly reflects the individual credit circumstances of the individuals when these loans were underwritten. Consequently additional variables representing loan terms were added to the performance residual regressions using the new account measure. These regressions were run at the level of individual account rather than individual borrower, as is the case with the other regressions.

Data in the credit records allow the classification of new loans along several dimensions: the type of lender—bank or thrift institution, finance company, credit union, and other (for example, retail stores); the type of loan—mortgage, auto, other installment, credit card, and other open-ended loans; largest amount owed; the month the loan was taken out; and, for mortgage loans and installment loans, the loan terms (loan maturity and monthly payment) and a derived estimate of the current interest rate.[18] Variables representing these items were added to the new account regressions.

Loan terms and interest rates also explain virtually none of the differences in performance residuals by race (table 8). The results hold when loan terms and interest rates are considered without other controls or along with other demographic and location factors. Thus, differences in the kinds of loans used by different races and the interest rates paid do not appear to be the source of differences in performance once credit score is taken into account.

Trigger Events

The credit literature refers to so-called "trigger or life-changing events" as causes of poor loan performance. These are shocks such as divorce, illness, or job loss which cause serious disruptions to an individual's economic circumstances and lead them to default on their credit obligations. Absent such shocks the individual would not default. One possible explanation of the racial and ethnic differences in scores and performance may be that blacks and Hispanic whites, which have lower scores on average than non-Hispanic whites, are more likely to experience trigger events.

There is indirect evidence that this might be the case which stems from the panel nature of our dataset. The data contain TransRisk credit scores at the beginning of the performance period (June 2003) and at the end, 18 months later (December 2004); the scores for both periods are normalized in the same way using the rank-order distribution of the June 2003 population.

A population group disproportionately subject to trigger events would be expected to exhibit greater reductions in credit scores than other groups.[19] However, if the reductions in scores are caused primarily by temporary trigger events, then scores of individuals in the

[18] Interest rates are not included in credit record data. However, for closed-end loans it is possible to estimate the current interest rate on the basis of items included in the data, including the size of the monthly payment, the amount borrowed, and the term of the loan. Such estimates have been made for installment and mortgage loans and assume that the loans are fully amortizing.

[19] Assessments of the importance of trigger events and other factors influencing loan performance are in Scott Fay, Erik Hurst, and Michelle J. White (2002), "The Household Bankruptcy Decision," *American Economic Review*, vol. 92 (June) pp. 706-18; and Li Gan and Tarun Sabarwal (2005), "A Simple Test of Adverse Events and Strategic Timing Theories of Consumer Bankruptcy," NBER Working Paper Series 11763 (Cambridge, Mass.: National Bureau of Economic Research, November).

lower credit score ranges would tend to rise over time, moving in the opposite direction as individuals recover (the increase in scores would likely be only gradual, as adverse information is removed from credit records only after a number of years). Put together, these forces should imply a regression to the mean for populations subject to temporary trigger events.

Changes in the TransRisk Score for individuals in each racial or ethnic group are shown in table 9. The mean score for virtually every group is little changed over the 18-month period. The mean score for the entire population increases only 0.1 percent. However, 17 percent of individuals experienced a credit score increase of 10 points or more and 17 percent experienced a decrease of 10 points or more. Significant changes in scores are relatively rare and not symmetric; 2.3 percent of individuals experienced a decline of 30 points or more, but only 1.6 percent of individuals experienced an increase of 30 points or more.

There is evidence, that overall, the population shows the patterns expected from trigger events; that is, over time, scores tend to migrate toward the middle of the distribution. For example, the scores of 71 percent of the individuals in the lowest score decile in June 2003 rose over the performance period, whereas the scores of only 23 percent of individuals in the top decile rose. However, the pattern of migration of scores toward the middle varies by subpopulation. Only in the lowest decile did the majority of blacks experience an increase in score; the majority of non-Hispanic whites experienced an increase in all but the top three deciles. Taken together, these data do not appear to offer a good explanation for racial and ethnic differences in scores. If the trigger event explanation is to hold, then either trigger events are persistent or happen more often to blacks than they do to other populations.

Other evidence on Income and Score

Unfortunately the data available for the analysis did not include a direct measure of the individual's income and we had to use a census tract-based estimate. An inference that individual's income could be an important factor in explaining racial and ethnic differences in scores and performance can be obtained from the census data. In the analysis above, about one-half of the difference in mean credit score between blacks and non-Hispanic whites could be explained by other demographics and a "fixed effect" for census tract. We mirrored this analysis using data on income derived from the 2000 Decenniel Census. For black households, mean income in 2000 was $38,700; for non-Hispanic white households, $56,870; and for Hispanic white households, $42,800. The $18,170 dollar difference in mean income between blacks and non-Hispanic whites is reduced to $9,800 when census tract location and age of household head are controlled for. The roughly $14,000 difference in income between non-Hispanic whites and Hispanics whites is reduced to $7,600 when census tract location and age are taken into account. So, like our analysis of score differences, about one-half of income differences between black and non-Hispanic white households is *within-tract* suggesting that is quite plausible that additional information on individual-level income might well explain at least a portion of the remaining score differences.

Using Neighborhood Composition as a Proxy for Individual Race and Ethnicity

When the racial and ethnic composition of the census block is used as a proxy for the race or ethnicity of the individual, the differences in mean credit scores across groups, although still substantial, are smaller than when the individual's race or ethnicity is derived from the SSA data. For example, when the census block proxy for race is used, the mean difference in the TransRisk Score between blacks and non-Hispanic whites falls from 28.4 points to 15.1 points; the mean difference between Hispanic whites and non-Hispanic whites falls from 15.8 points to 9.6.

Similar reductions in performance residuals differences across racial and ethnic groups are observed when the census block race or ethnicity proxy is used. The mean any account TransRisk performance residual for blacks falls from 5.6 percent to 3.4 percent and for Hispanics whites it falls from 1.9 percent to 1.1 percent. Mean new account residuals fall from 2.6 percent to 1.6 percent for blacks and for Hispanics whites it actually rises from .1 to .3.

The multivariate results show similar patterns. The signs of the differences are the same as when individual race variables are used but differences are muted. For example, the analysis using the census block proxy for race finds an unexplained difference of 2.5 points between non-Hispanic whites and blacks. In contrast, an unexplained difference of 13.4

points remains between these two groups when the individual's race or ethnicity is used in the analysis.

These results suggest that locationally-based proxies for race or ethnicity are imperfect substitutes for individual race. The explanation for this may lie in the observation noted above, that one-half of the black-white difference in credit scores is *within-tract*. Perforce, such differences cannot be detected by a census tract-based proxy. Our use of block-based racial and ethnic measures will pick up some of the within-tract differences, but as just shown, a significant within-neighborhood differences must remain.

V. The Consequence of Credit Scores--Credit Availability and Affordability

The credit-record data assembled for this study can be used to investigate the effects of credit scores on the availability and affordability of credit. However, there are a number of issues that need to be addressed in such an investigation. The first issue in using credit record data for this purpose is that we observe an individual's credit score at a particular point in time. Unfortunately, the timing of new credit acquisition does not necessarily correspond to the same point in time at which the credit scores used in the study were calculated. As discussed in the previous section, some of the timing issues can be mitigated by focusing on new credit issued within a short period of time after the credit score was calculated.

The second issue is that we only observe in credit records actual extensions of new credit. The incidence of new credit is effected by both demand and supply factors. Thus, some individuals do not receive new credit because they do not want or need it, others because they believe they would be turned down and are discouraged from applying, and others because they have applied but are denied. Ideally, one would like to isolate the latter two effects, which are direct reflections of the availability of credit. There is no direct data on denials in the credit record data; however, there is a method employed by the industry to proxy for denials that derives from a review of credit inquiry patterns. Credit inquiries arise when an individual has sought credit and the prospective lender pulls the individual's credit record to evaluate their current financial circumstances. Thus, credit inquiries observed during a period when an individual does not receive credit are taken as indicators of loan denials.[20]

A third issue is that credit record data does not provide direct information on the pricing of credit. For open-ended credit, there is no loan term information provided at all in the credit records. For closed-ended credit, the credit records provide information on the loan terms at the time the credit report was drawn, which, as shown earlier, can be used to estimate interest rates. However, for adjustable-rate loans or for loans for which there were substantial upfront points or fees, interest rates calculated in this way may not reflect the full pricing of credit.

Subject to these caveats, the approach taken to address affordability and availability parallels that used previously to address issues in loan performance. Specifically, we examine the relationship between TransRisk Scores in our sample measured in June 2003 and three measures of availability and affordability of credit, as measured over the July 2003 to December 2003 period: Issuance of any new credit (evidence of availability); credit inquiries without the issuance of new credit (evidence of denial); and interest rates on new closed-end credit (evidence on affordability). These comparisons are made for different racial or ethnic groups and, where possible, for different loan types.

The credit-record data reveal relatively few differences across racial or ethnic groups in the incidence of new credit after controlling for credit score quintile (shown earlier in table 8). Black borrowers were somewhat less likely than others to take out new mortgages and automobile loans from banks and generally to open credit card accounts but were more likely to take out new installment loans at finance companies. Differences were most pronounced in the lowest two credit-score quintiles. For each credit-score quintile, black and Hispanic white borrowers have a higher incidence of denial than non-Hispanic whites. Estimated interest rates also differ across racial and ethnic groups after controlling for loan type and credit score quintile. Black borrowers experienced higher interest rates than non-Hispanic whites for each loan category in which interest rates can be determined, although, as noted, some differences were small.

[20] Inquiries in the absence of new credit is an imperfect proxy for denials, as the lack of new credit may reflect a decision by a prospective borrower not to borrow (for example, they may have withdrawn their loan application) rather than a denial of credit. Further, the inquiry might be associated with a loan taken out at a later point in time.

The tables just presented may mask effects due to variation within credit score quintiles. In order to provide a better measure of the continuous relationship between credit scores and the three measures of availability and affordability of credit, figures were constructed showing the continuous relationship between the TransRisk Score and the incidence of new credit, the incidence of the denial proxy, and estimated interest rates.

For each racial and ethnic group, there is a “u-shaped” relationship between credit scores and the incidence of new credit (figure 5). The decline in the incidence of new credit at higher credit score levels is almost surely due to demand, rather than supply, factors. Individuals with higher scores are less likely to desire or need new credit. At the lower end of the credit score range, the upward sloping incidence of new credit is much more likely to reflect differences in supply. The patterns for different groups appear to be quite similar. The incidence of denial, as proxied by the inquiry measure, uniformly declines in credit scores for each group (figure 6). Moreover, both the shapes and levels of the curves appear to be quite similar.

Similarly, estimated interest rates show a monotonically decreasing relationship with credit scores, again with the curves for different racial and ethnic groups exhibiting similar slopes and levels, although auto loan rates for black borrowers appear to be somewhat higher than for individuals of other races with similar credit scores (figures 7a,b,c). The slopes of the curves do vary across loan products, with interest rates for mortgages showing a flatter pattern than for automobile credit or other loans. The relationships for credit scores and other installment loan interest rates appear to be much less consistent than those for mortgage or automobile loans. This is likely due to the fact that the collateral for other installment loans is more heterogeneous and the loan category incorporates a wider range of products.

To address whether population differences between these curves can be narrowed when other factors are controlled for, a multivariate analysis was conducted. The analyses are similar to those conducted for loan performance and include the same demographic characteristics and control factors, specifically, credit score and location.

The dependent variable for the first analysis is the incidence of new credit. Following the approach used for the performance residuals, a regression equation was fitted with dummy variables for race with the non-Hispanic white population serving as the base group. The analysis reveals that differences in the incidence of new credit across racial or ethnic groups largely disappear once credit score and other factors are taken into account (table 10). A second multivariate analysis was conducted for the inquiry-based proxy for loan denial. Here, the higher incidences shown for black and Hispanic white individuals are largely unaffected by controls for other factors (table 11).

The third set of multivariate analyses focused on the interest rates for new mortgage and auto loans.[21] The multivariate regressions were virtually identical to those in the previous section except that the dependent variable was the loan interest residuals rather than loan performance residuals and, perforce, the sample for the interest rate analysis was limited to loan products for which interest rates could be calculated. Multivariate results suggest that little of the racial and ethnic differences in interest rates can be explained by loan type, lender, and amount and the demographic and location controls considered here (tables 12 and 13).[22] The gross mortgage interest rate difference between blacks and non-Hispanic whites was 0.39 percentage points after controlling for score; the difference was still 0.39 percentage points after loan terms and lender type were taken into account. (Auto loan rate differences across racial and ethnic groups widen when other factors are taken into account.) The difference narrowed to 0.26 percentage points, when demographic and location controls were taken into account.[23]

VI. Conclusions and Qualifications

Credit scoring is a statistical technology that has helped reduce the cost and time of credit evaluation and increased access to credit for the population as a whole. While the broad benefits of credit scoring as one measure of the creditworthiness of individuals are generally recognized, concerns remain about the effects of this technology on different populations. Using a unique set of data that combines credit records and personal demographic information many aspects of these concerns are addressed.

---

[21] Regressions for other new installment loans were estimated but are not presented. This loan category was quite heterogeneous and estimation results were not robust.

[22] As noted, the interest rate analysis conducted here is limited to the data included in credit records and consequently does not account for all factors creditors consider in pricing credit (for example, debt-to-income ratios, loan-to-value ratios, loan size and collateral status).

[23] An additional analysis was conducted using the amount borrowed, rather than the interest rate of the loan, as the dependent variable. All new loans could be used in that analysis because balances were reported for all loans. Results, not shown in the tables, indicate little difference across groups in the amounts borrowed once credit score and the type of loan and lender are taken into account.

First, using the two commercially-available generic credit history scores available to this study, we find that the credit scores of blacks are consistently below those of white non-Hispanic whites or Hispanics whites, with the scores of Hispanic whites falling between those of blacks and non-Hispanic whites. These differences can only be partially explained by differences in age, marital status, income, and neighborhood (census tract). Indeed, the within-tract difference in creditworthiness between blacks and non-Hispanic whites is more than one-half of the overall difference, suggesting that blacks and non-Hispanic whites living in the same neighborhood can be expected to have substantially different measures of creditworthiness.

Second, differences between blacks and non-Hispanic whites in credit performance appear to be consistent with differences in measures of creditworthiness. That is, all else equal, a black borrower would be expected to perform worse (have a higher level of loan default) than a non-Hispanic white borrower with the same credit score. Everything else the same, this result suggests that lenders might have an economic incentives to discriminate by charging black borrowers higher interest rates (or having higher deny rates for black applicants) than white borrowers with comparable assessments of creditworthiness (as measured by credit scores). However, examination of loan denial patterns and interest rates on closed-end credit, suggests that fears of such actions may, for the most part, be unfounded. Conditioned on credit score, interest rates charged to black borrowers are only marginally greater than those charged to comparable non-Hispanic white borrowers, with differences significantly less than might be expected if differences in loan performance were taken into account.

Third, the overall life cycle patterns of credit scores and loan performance of blacks and whites appear to be quite similar. Credit scores for individuals of both racial and ethnic groups precipitously drop within the first several years following entry into the credit market, reflecting the fact that individuals in their early twenties show extraordinarily high levels of loan default. From this low level, credit scores and loan performance steadily rise throughout the lifetime, peaking in the late seventies. The major difference in the life cycle patterns of blacks and whites is that the initial fall in credit scores after entering the credit market is much larger for blacks than that of non-Hispanic whites. Thereafter, rates of improvement for the two groups are similar (a little lower for blacks); but because blacks are starting at a much lower level, their expected loan performance and measures of creditworthiness are consistently below that of comparably-aged non-Hispanic whites.

Finally, locationally-based (census block group) measures of race or ethnicity appear to only imperfectly proxy for true individual race and ethnicity. Racial and ethnic differences in credit scores and performance were consistently understated when census-block measures of race and ethnicity were used relative to those derived from the SSA data. A likely cause of this understatement is the large within-tract differences in credit scores.

Taken together, these results suggest that there are differences in credit usage and loan performance, between blacks and non-Hispanic whites which cannot be explained by income, age or other identifiable socio-economic factors. Ultimately, these differences result in predictable differences in the access to and pricing of credit which can indirectly effect other measures of well being such as homeownership and wealth accumulation.

There are a number of policy implications from these results. The results suggest that efforts to “close the gap” between racial and ethnic groups may need to start very early, perhaps with high school financial literacy education. Many young individuals are sowing the seeds for higher lifetime credit costs by impairing their credit at an early stage. Avoiding these early “mistakes” may do more to reduce lifetime borrowing costs and narrow score gaps between the races than any other policy prescription.

There are also implications for fair lending. The data suggest that there may be economic incentives for lenders to charge blacks higher prices (or deny them at higher rates). Such actions are illegal under the nation’s fair lending laws. However, because such behavior may be economically profitable, it is important that fair lending laws be vigorously enforced to better ensure a level playing field. It is encouraging that in the data examined here there is relatively little evidence of interest rate and denial rate differences controlling for score. However, settlements and enforcement actions with lenders regarding alleged fair lending violations continue still occur suggesting that discriminatory behavior has not been eliminated.

The study for which this paper was drawn was the most comprehensive examination of the relationship between race, creditworthiness and loan performance to date. Nevertheless there are a number of important caveats to bear in mind in evaluating our results. First, we only looked at credit history scores. The underwriting and pricing of many loans, including home mortgages and autos, is based on a fuller set of information than data in credit records. Our conclusions may not carry over to these more comprehensive measures of creditworthiness. Second, we lacked data on important control variables, such as accurate estimates of income, employment, marital and health history which may be important determinants of loan performance. Nor do we know, beyond our limited look at closed-end loan interest rates, if the lenders serving different demographic groups are offering similar terms and service. These are important omissions. Ultimately, since credit scores and creditworthiness, are determined to a large extent by past loan performance, it is only by understanding and changing the root causes of performance differences that we can begin to equalize credit access and pricing across races.

References

Table 1. Number of Selected Credit-Record Items in Full Sample and Their Proportion in the Scorable Sample

Percent except as noted

Characteristic	Full Sample (Number)					Scorable Sample							
	Total	No Score Available	Mean Trades	Score Available	Mean Trades	Revolving Account	Install-ment Account	Mort-gage Account	Public Record	Medical Collect-ion	Other Collect-ion	Inquiry	90+ Delin-quency on Any Account
SSA Race													
Non-Hispanic White	162,932	14,364	10.2	148,568	16.4	88.3	45.2	33.8	12.9	14.7	14.5	75.9	14.6
Black	25,937	4,569	3.8	21,368	13.0	65.8	46.6	21.1	27.1	35.4	47.9	86.1	34.9
Hispanic	19,446	2,496	5.8	16,950	13.7	80.6	45.5	28.0	14.9	21.5	28.9	84.0	22.8
Asian	9,675	855	12.8	8,820	15.5	91.6	35.4	31.3	9.1	7.5	11.6	77.1	12.5
American Indian	441	32	11.2	409	15.8	90.7	41.2	30.9	12.4	12.3	11.6	67.8	13.5
Unknown Race	83,106	46,754	1.0	36,352	9.7	80.2	27.6	18.8	8.8	11.0	14.0	52.7	11.9
Racial Distribution of Block													
Block Percent N-H White	218,053	43,966	4.1	174,087	15.3	86.4	42.9	31.4	12.7	15.1	15.7	73.4	15.0
Block Percent Black	35,151	11,205	2.0	23,946	12.9	74.3	41.0	22.9	19.8	24.9	32.5	76.4	25.1
Block Percent Hispanic	34,222	10,589	2.2	23,632	13.1	80.5	40.3	25.2	14.1	18.1	25.1	75.5	19.6
Block Percent Asian	11,670	2,654	3.7	9,016	14.5	87.5	37.1	29.7	12.0	10.8	16.2	72.6	14.7
Block Percent Amer Ind	1,875	502	2.6	1,373	13.9	78.5	46.7	24.6	14.9	20.0	23.4	75.2	20.9
Total	301,536	69,069	3.5	232,467	14.8	84.5	42.2	29.8	13.5	16.2	18.4	73.8	16.6

Table 2. Distribution of Race and Ethnicity in the U.S. Population and the Sample Population
Percent

Race or ethnicity	U.S. Population	Unknown Race Excluded			Unknown Race Imputed		
		Full Sample	No Score Available	Score Available	Full Sample	No Score Available	Score Available
Non-Hispanic White	73.0	74.6	64.4	75.8	72.5	63.9	75.0
Black	11.3	11.9	20.5	10.9	12.5	17.7	10.9
Hispanic	11.1	8.9	11.2	8.6	10.2	13.9	9.1
Asian	3.9	4.4	3.8	4.5	4.6	4.3	4.7
American Indian	0.7	0.2	0.1	0.2	0.2	0.2	0.2
Total	100	100	100	100	100	100	100

Note. Race and ethnicity in the sample are as determined from records of the Social Security Administration. For details of imputation, refer to text.

Table 3.Score Statistics and Distribution, by Race and Ethnicity

Selected characteristic	Score Statistics				Percent Distribution by Overall Score Decile									
	Sample	Mean	Median	Std Dev	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
TransRisk Score														
SSA Race														
Non-Hispanic White	148,568	54.0	55.0	28.7	7.8	8.5	8.7	9.9	10.1	10.0	9.7	10.6	12.7	12.0
Black	21,368	25.6	19.8	22.8	30.1	22.5	15.6	10.1	7.2	4.6	3.2	2.7	2.4	1.7
Hispanic	16,950	38.2	33.8	26.0	15.1	15.0	14.9	13.3	10.8	9.5	6.8	5.6	5.0	4.0
Asian	8,820	54.8	55.6	26.2	5.7	6.6	7.3	10.6	12.0	14.0	12.4	11.1	10.6	9.8
American Indian	409	57.6	60.6	28.8	5.6	8.5	7.7	9.2	9.7	9.1	8.6	11.8	14.7	15.1
Unknown Race	36,352	52.7	56.0	26.1	6.6	7.6	9.5	8.9	10.7	11.8	16.6	13.2	7.5	7.6
Total	232,467	50.1	50.0	28.9	10.1	10.1	9.8	10.1	10.1	9.9	10.0	10.0	10.3	9.7
VantageScore														
SSA Race														
Non-Hispanic White	148,568	54.5	56.6	28.7	7.5	8.3	9.0	9.6	9.3	9.4	10.3	11.7	12.5	12.2
Black	21,368	26.0	19.0	23.3	30.2	21.9	15.1	10.1	6.9	5.0	3.8	2.9	2.1	2.0
Hispanic	16,950	38.6	34.0	26.2	14.9	14.9	15.1	12.4	10.9	9.1	7.4	6.3	4.7	4.2
Asian	8,820	55.7	56.4	26.7	4.9	6.7	8.4	10.5	11.8	12.0	11.5	11.8	10.5	11.9
American Indian	409	58.2	63.0	27.7	5.7	6.2	9.0	8.2	8.9	9.5	10.4	13.9	15.2	13.1
Unknown Race	36,352	49.3	50.8	25.4	8.1	8.3	8.4	10.6	13.4	15.4	14.4	8.5	6.9	6.0
Total	232,467	50.0	50.0	28.9	10.1	10.0	9.9	10.0	10.0	10.0	10.2	10.0	10.0	9.7

Table 4 Mean Performance Measures (Percent Bad), June 2003 to December 2004

Selected characteristic	Any Account		Modified New Account	
	Sample	Mean	Sample (Accts)	Mean
SSA Race				
Non-Hispanic White	133,165	22.6	86,628	2.5
Black	18,274	65.9	9,430	10.5
Hispanic	14,702	42.0	10,194	4.7
Asian	7,906	18.2	6,062	2.3
American Indian	366	18.6	198	2.4
Unknown Race	26,024	24.4	12,206	3.6
Total	200,437	28.0	124,719	4.5

Table 5 Performance Residuals (Unexplained Percent Bad), June 2003 to December 2004

Selected characteristic	Any Account	Modified New Account
TransRisk Score		
SSA Race		
Non-Hispanic White	-1.0	-0.4
Black	5.6	2.6
Hispanic	1.7	0.1
Asian	-2.1	0.0
American Indian	-2.1	-0.5
Unknown Race	0.8	0.4
Total	0.0	0.0
VantagageScore		
SSA Race		
Non-Hispanic White	-0.7	-0.3
Black	6.0	2.6
Hispanic	1.9	-0.1
Asian	-2.1	0.0
American Indian	-1.0	-0.3
Unknown Race	-0.8	0.3
Total	0.0	0.0

Table 6 Regression estimates of TransRisk Score differences

Difference from Non-Hispanic White Base Group

	Gross	Control For Age, Marital Status	Plus Tract
SSA Race			
Black	-28.3	-22.8	-13.4
Hispanic	-15.7	-9.6	-3.9
Asian	0.9	6.8	5.5

Table 7 Regression estimates of TransRisk Loan Performance Differences

Difference from Non-Hispanic White Base Group

	Gross	Control For Age, Marital Status	Plus Tract
Any Account			
SSA Race			
Black	6.6	6.9	4.7
Hispanic	2.7	2.7	1.4
Asian	-1.1	-1.5	-1.2
New Account			
SSA Race			
Black	3.0	3.3	2.1
Hispanic	0.5	0.4	-0.3
Asian	0.3	0.1	0.0

Table 8 Regression estimates of TransRisk Loan Performance Differences, Account Level

Difference from Non-Hispanic White Base Group

	Gross	Control For Loan Terms	Plus other Variables
New Account, Account Level			
SSA Race			
Black	3.0	3.2	1.6
Hispanic	0.5	0.4	-0.5
Asian	0.3	0.0	-0.2

Table 9. Changes in TransRisk Score, June 2003 to December 2004

Selected characteristic	2003 Score	2004 Score	Change Mean	Change %Up	Score Changes by Points <-30	-30 to -10	-10 to -5	-5 to 5	5 to 10	10 to 30	>30	Percent of Scores Rising by 2003 Score Decile 1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
SSA Race																					
Non-Hispanic White	54.1	54.3	0.2	50.9	2.3	14.3	10.2	42.9	12.7	16.1	1.6	72.8	57.4	56.7	57.5	56.0	56.4	53.6	48.8	41.5	23.0
Black	25.7	25.8	0.1	52.2	1.5	13.1	9.8	48.0	13.3	13.3	1.0	68.5	48.4	43.9	46.2	45.8	44.9	45.1	40.9	36.0	19.1
Hispanic	38.4	38.5	0.2	52.4	2.3	15.1	10.1	41.0	13.6	16.5	1.5	70.4	53.4	54.5	52.4	52.0	49.1	45.4	43.3	38.7	22.9
Asian	54.9	55.7	0.9	53.2	2.6	14.2	9.6	39.6	13.1	18.8	2.2	70.9	62.5	62.2	60.8	61.2	56.6	51.4	47.5	44.4	25.3
American Indian	57.7	58.1	0.4	51.5	2.8	12.1	10.1	44.5	12.8	15.7	2.1	77.4	64.9	63.8	60.5	58.4	58.5	55.9	49.3	43.1	21.7
Unknown Race	52.8	52.3	-0.5	50.6	2.9	14.5	10.8	44.3	12.2	13.8	1.6	70.7	57.3	58.2	54.9	56.0	56.6	52.8	42.5	35.5	20.3
Total	50.1	50.3	0.1	51.2	2.3	14.2	10.2	43.3	12.8	15.6	1.6	71.1	55.3	55.0	55.7	55.2	55.5	52.6	47.1	40.8	22.7

Table 10. Characteristics of New Loans for Borrowers, July-December 2003

Selected characteristic	Percent w/loans	Est. Denial rate	Mortgages			Auto/Bank			Auto/Fin			Install/Bank			Install/Fin			CC/Bank		CC/Fin		Other	
			% Loans	Rate	%Bad	% Loans	Rate	%Bad	% Loans	Rate	%Bad	% Loans	Rate	%Bad	% Loans	Rate	%Bad	% Loans	%Bad	% Loans	%Bad	% Loans	%Bad
Lowest Qunitle																							
SSA Race																							
Non-Hispanic White	18.7	40.2	11.4	9.3	3.9	6.3	10.7	4.3	10.7	16.4	6.4	7.6	11.4	6.2	18.2	19.1	13.3	33.5	22.1	1.4	8.7	11.0	20.8
Black	17.9	44.9	7.9	9.4	4.8	3.7	14.1	4.6	11.4	17.6	11.2	5.7	14.6	6.0	28.2	20.5	14.8	31.0	35.5	1.4	27.6	10.7	29.4
Hispanic	17.9	43.4	8.2	9.6	1.9	3.9	11.1	10.8	9.1	16.4	8.6	3.7	12.4	3.9	32.4	22.5	17.6	28.3	20.2	2.7	19.7	11.6	14.8
Asian	19.1	41.9	10.2	9.0	3.6	4.7	10.9	7.5	7.6	15.3	4.9	5.0	9.8	7.1	10.9	19.9	25.9	45.5	17.5	2.6	2.0	13.6	11.2
American Indian	21.4	38.0	7.5	9.2	7.2	4.8	11.6	2.8	5.2	15.2	7.1	6.8	10.4	3.8	26.0	17.6	8.8	32.9	28.6	1.1	4.9	15.7	11.1
Unknown Race	13.6	36.3	9.0	8.8	3.2	5.8	12.3	8.2	9.8	16.0	6.8	6.0	13.0	7.9	19.9	19.3	17.1	35.0	26.8	0.9	0.0	13.7	17.9
Total	17.9	41.3	10.0	9.3	3.8	5.3	11.5	5.4	10.5	16.6	7.9	6.5	12.2	6.1	22.2	19.9	14.9	32.7	25.2	1.5	14.3	11.3	21.4
2nd Quintile																							
SSA Race																							
Non-Hispanic White	42.0	19.4	16.4	8.3	1.4	8.7	7.6	1.5	4.2	12.2	2.3	6.4	10.4	1.8	8.9	19.7	6.1	29.2	7.2	2.4	5.4	23.8	3.9
Black	36.8	23.9	12.9	8.7	3.0	6.1	8.7	2.3	4.9	13.8	10.2	5.6	12.8	4.5	17.9	22.0	7.5	25.3	13.9	1.6	8.6	25.7	10.2
Hispanic	42.6	22.8	12.4	8.5	1.4	6.0	8.2	1.4	4.2	11.6	2.1	4.4	12.4	3.4	12.6	22.7	6.9	27.6	7.6	2.7	1.0	30.0	5.8
Asian	44.8	19.1	16.7	7.9	2.8	6.1	6.8	1.3	2.7	10.5	2.9	2.7	10.6	9.0	4.7	19.6	3.7	37.9	5.4	2.4	6.4	26.7	7.2
American Indian	36.5	16.1	14.3	8.2	0.4	7.8	7.1	0.2	5.8	8.8	1.2	9.4	10.9	0.9	12.2	21.0	3.8	26.7	4.0	2.5	1.0	21.2	2.6
Unknown Race	27.2	16.3	15.0	8.4	2.2	7.0	8.1	2.4	4.7	13.0	2.1	6.2	10.1	2.7	10.6	20.0	8.7	30.5	7.8	2.1	6.4	24.0	5.2
Total	39.4	19.8	15.4	8.3	1.7	7.8	7.8	1.6	4.3	12.4	3.3	5.9	10.8	2.5	10.4	20.5	6.7	29.1	7.9	2.3	5.2	24.9	5.2
Top Three Quintiles																							
SSA Race																							
Non-Hispanic White	39.1	8.0	20.8	7.6	0.1	8.7	5.7	0.3	2.5	6.9	0.7	4.5	8.2	0.5	1.8	15.2	2.0	27.1	1.1	3.8	0.4	30.9	0.7
Black	39.0	11.4	17.3	8.4	0.2	7.1	6.6	1.4	2.2	7.9	0.0	4.6	10.6	2.2	4.4	19.9	5.3	29.1	4.2	2.9	2.3	32.4	1.7
Hispanic	43.3	10.4	18.7	7.8	0.3	7.7	6.4	0.5	2.4	9.2	1.6	3.2	9.1	2.5	3.3	18.0	2.5	27.3	2.1	3.3	1.2	34.2	1.6
Asian	42.2	9.9	20.9	7.0	0.2	6.5	5.6	0.4	1.7	6.9	0.0	2.5	8.3	0.0	1.2	15.0	0.1	33.9	0.8	2.7	1.7	30.6	1.2
American Indian	32.8	6.6	20.3	7.6	0.3	10.9	6.1	0.1	3.2	7.0	0.1	7.6	9.2	0.1	2.5	11.2	1.2	26.5	2.2	3.2	0.2	26.0	0.4
Unknown Race	20.5	6.4	18.5	7.6	0.1	7.3	6.2	0.5	2.4	7.2	1.0	4.0	8.4	0.3	2.0	16.5	1.2	29.5	2.0	3.7	2.0	32.6	1.0
Total	36.2	8.0	20.3	7.6	0.2	8.3	5.8	0.4	2.5	7.2	0.7	4.2	8.4	0.6	2.0	16.1	2.2	27.8	1.4	3.6	0.7	31.3	0.9

Table 11 Regression estimates of Differences in New Account Acquistion, Person Level

Difference from Non-Hispanic White Base Group

	Score Only	Control For ‚ge, Sex marit‹	Control For Plus Tract
SSA Race			
Black	-2.3	-0.4	1.1
Hispanic	0.4	0.3	1.3
Asian	1.8	-0.2	-0.7

Table 12 Regression estimates of Differences in Denial Rate Proxy, Person Level

Difference from Non-Hispanic White Base Group

	Score Only	Control For ge, Sex marit	Control For Plus Tract
SSA Race			
Black	2.5	2.7	2.6
Hispanic	2.1	1.8	1.7
Asian	1.4	0.6	0.4

Table 13 Regression estimates of Mortgage Loan Interest Rate Differences, Account Level

	Difference from Non-Hispanic White Base Group		
	Score Only	Control For Loan Terms	Control For All Variables
SSA Race			
Black	0.39	0.39	0.26
Hispanic	0.19	0.19	0.21
Asian	-0.58	-0.32	-0.30

Table 14 Regression estimates of Auto Loan Interest Rate Differences, Account Level

Difference from Non-Hispanic White Base Group

	Gross	Control For Loan Terms	Control For All Variables
SSA Race			
Black	1.47	1.33	2.17
Hispanic	0.68	0.60	0.68
Asian	-0.37	-0.08	-0.01

Figure 1.A. TransRisk Score: Any-Account Performance (Percent Bad)

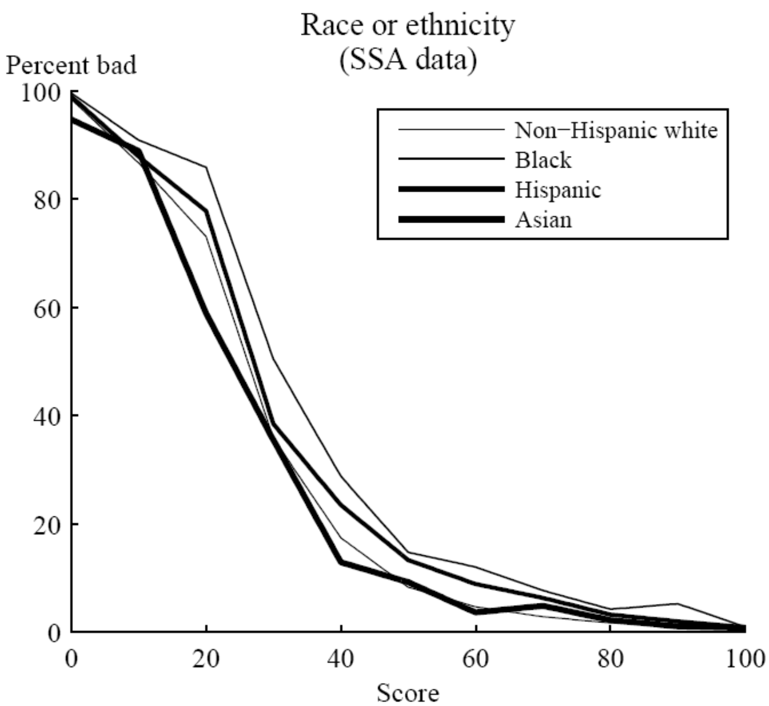

Figure 1.B. TransRisk Score: New-Account Performance (Percent Bad)

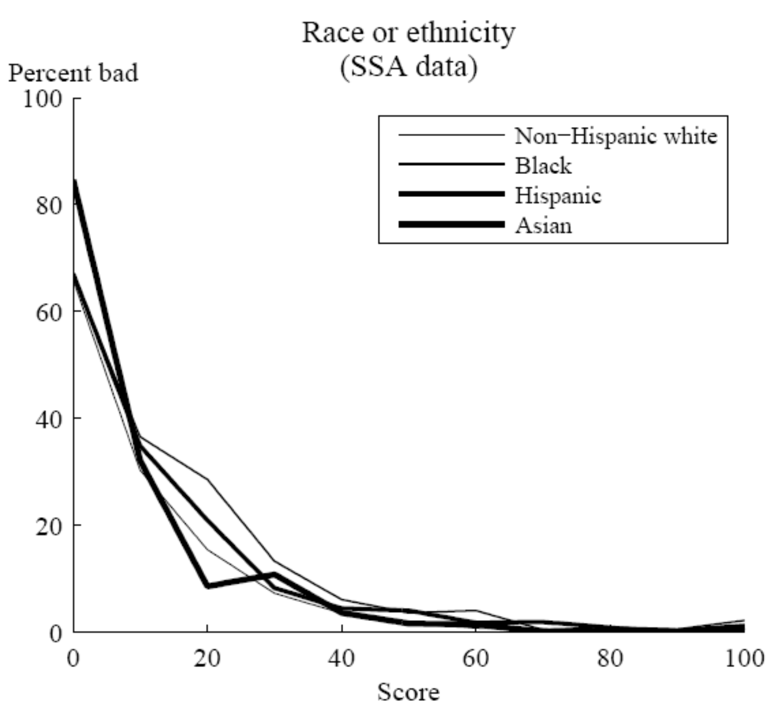

Figure 2: TransRisk Score by Age

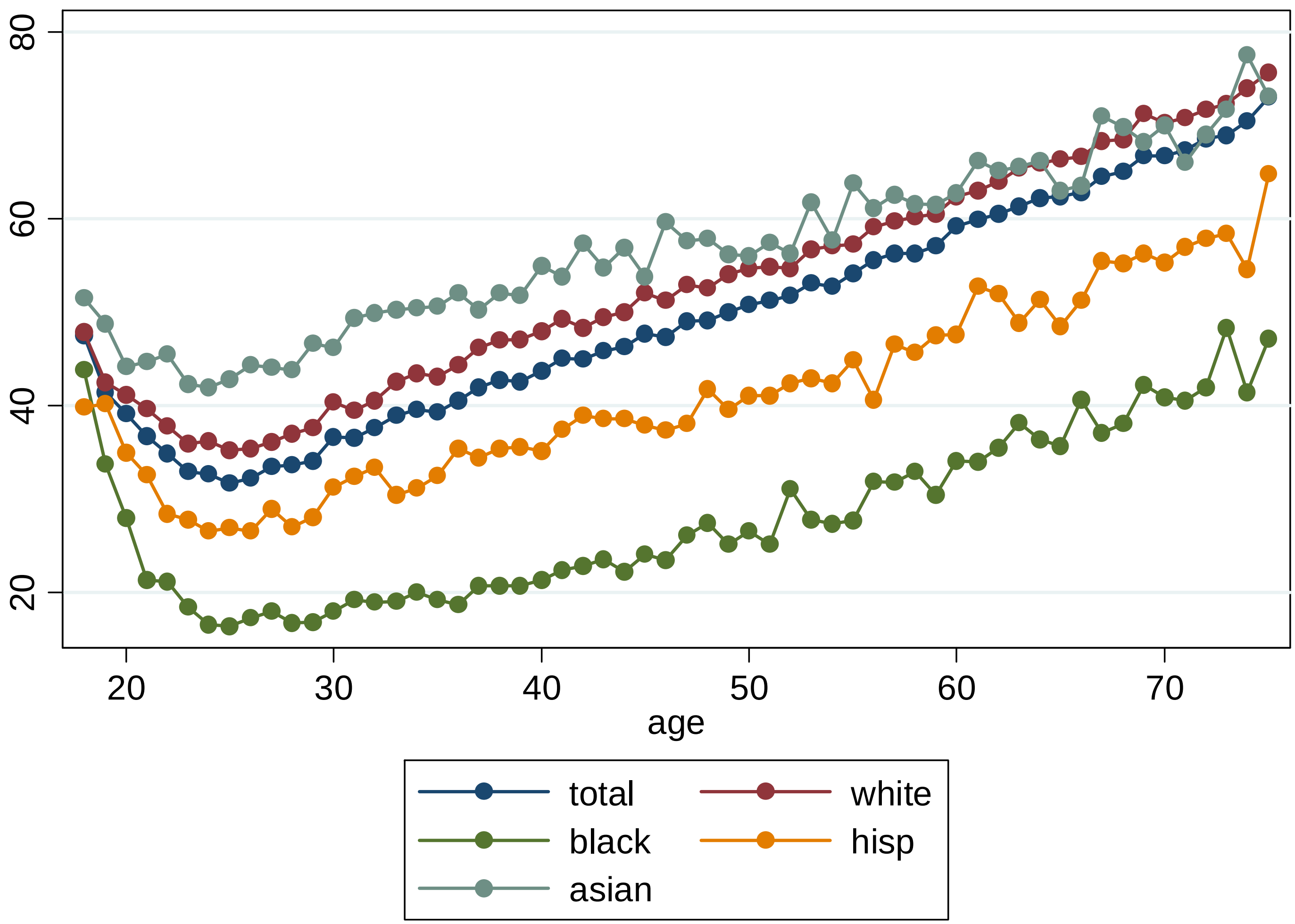

Figure 3(a): Performance on Any Account

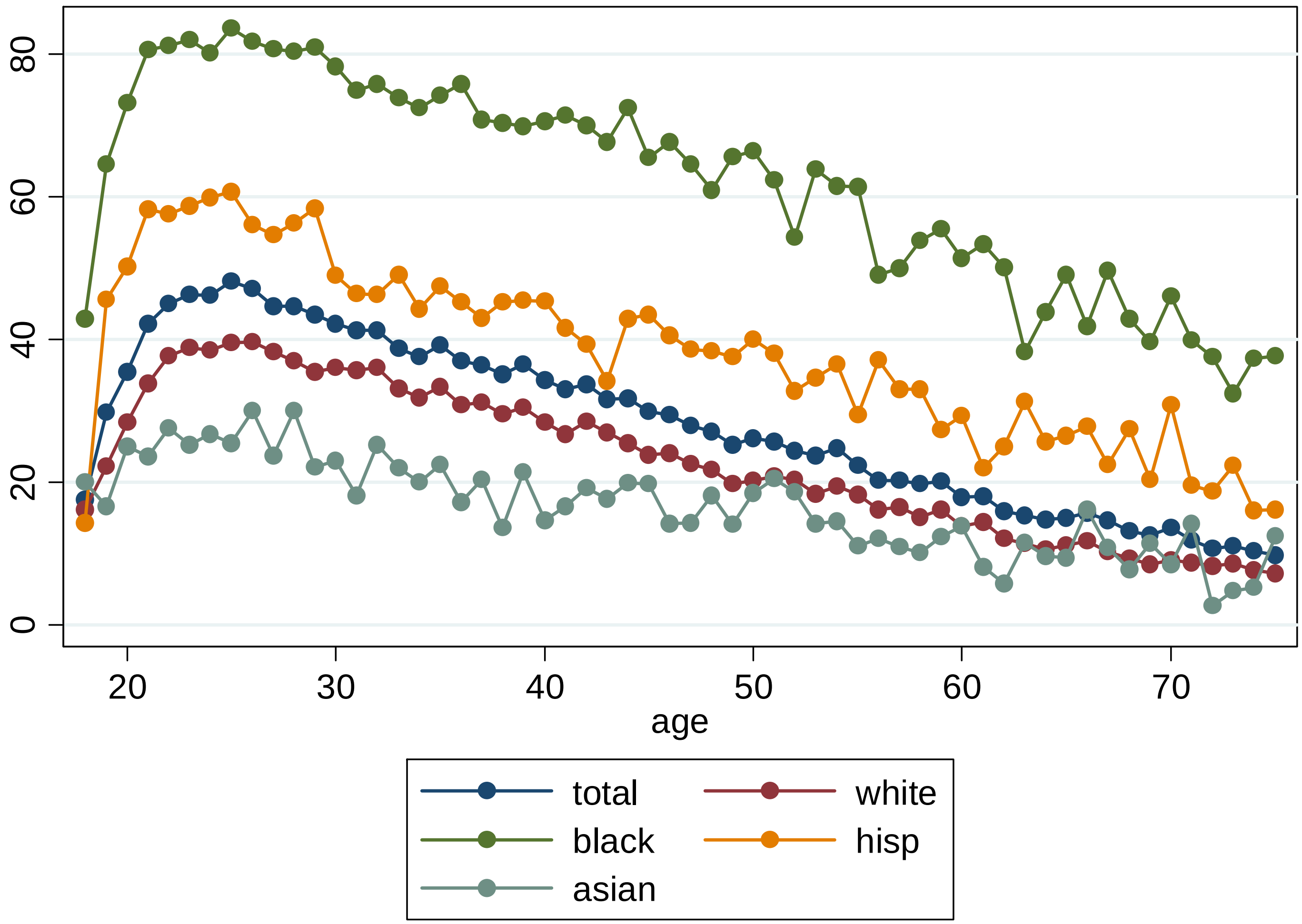

Figure 3(b): Performance on New Credit

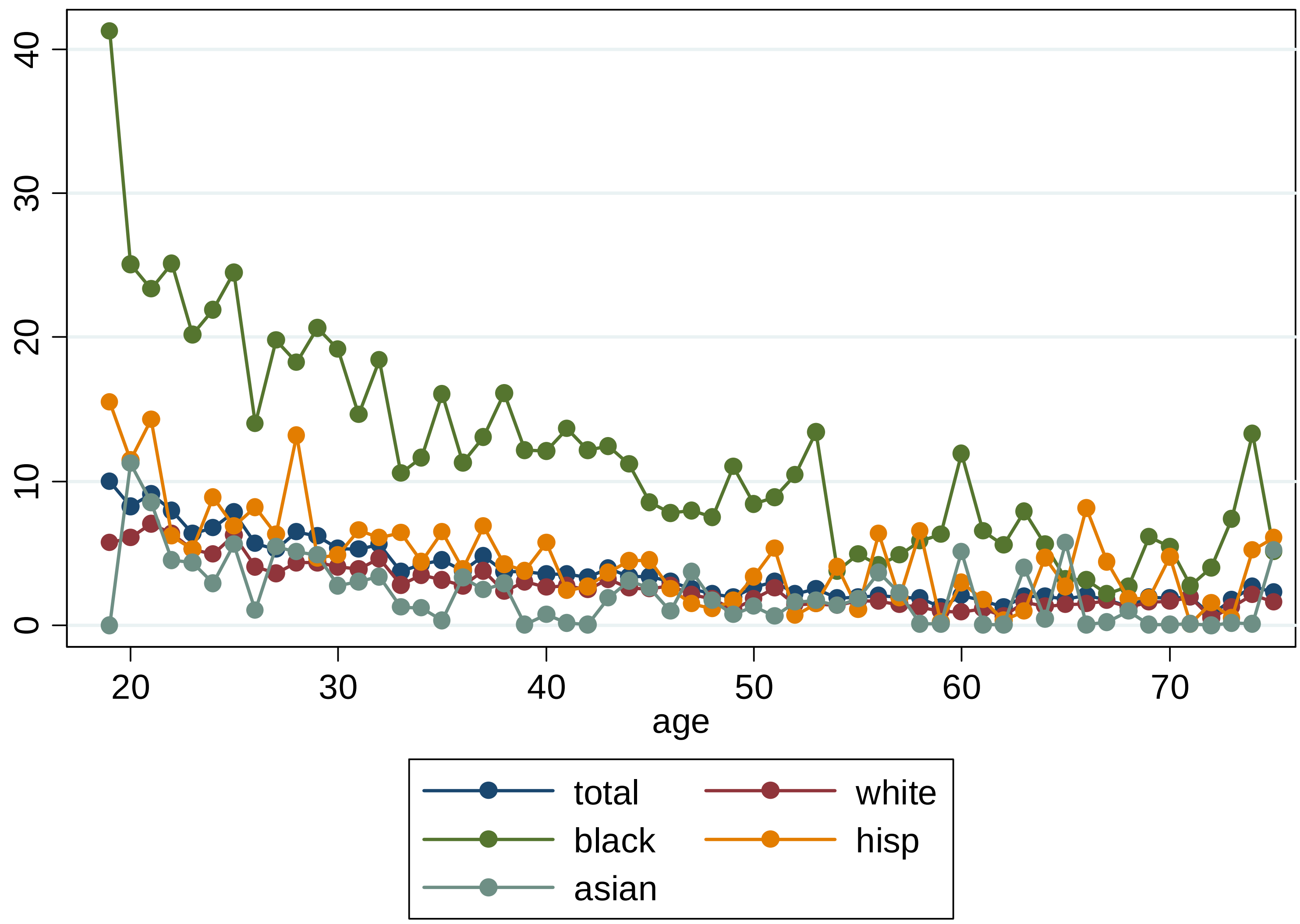

Figure 4: Any Account Performance Residual

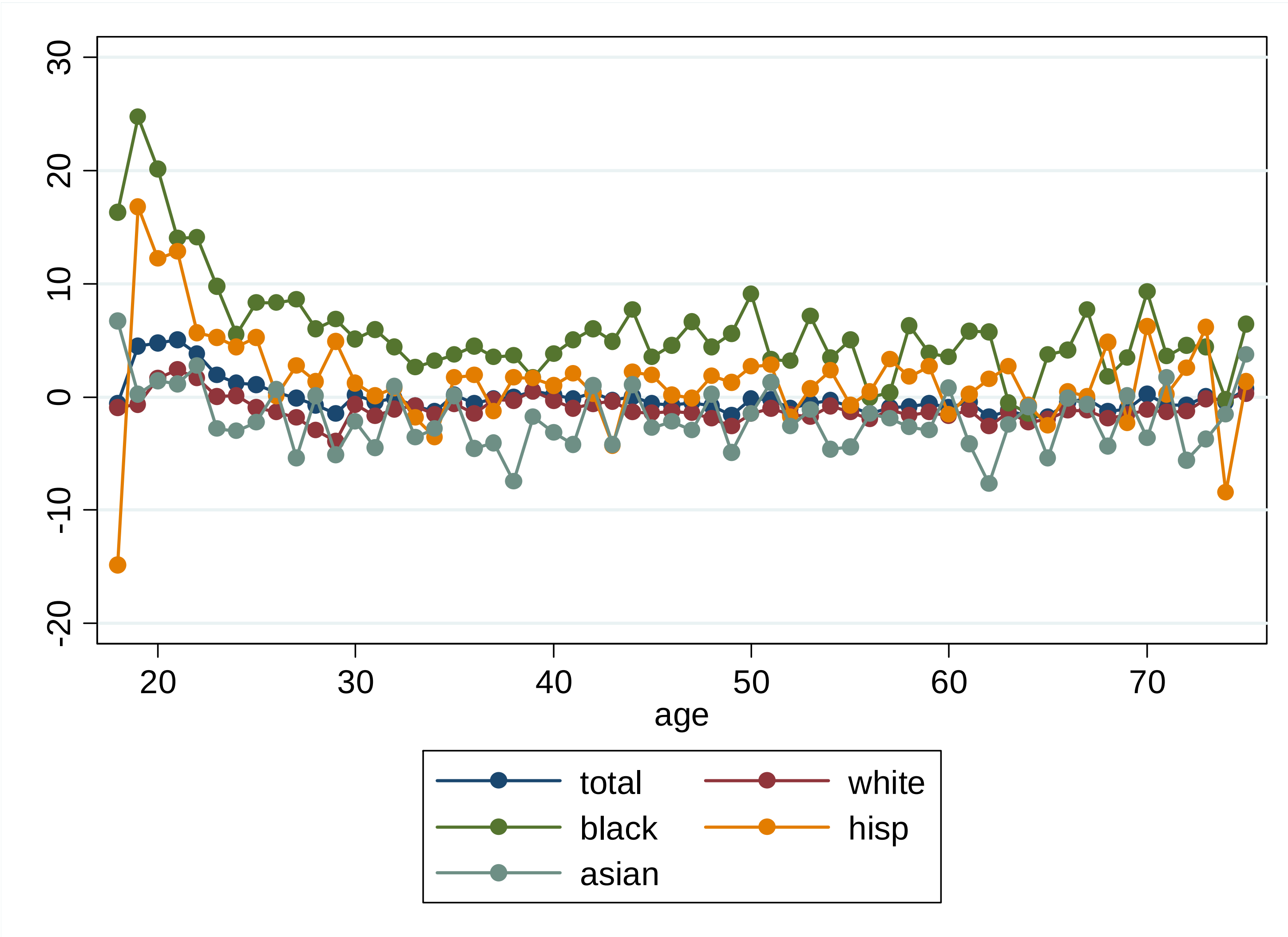

Figure 5. TransRisk Score: New Account Acquisition

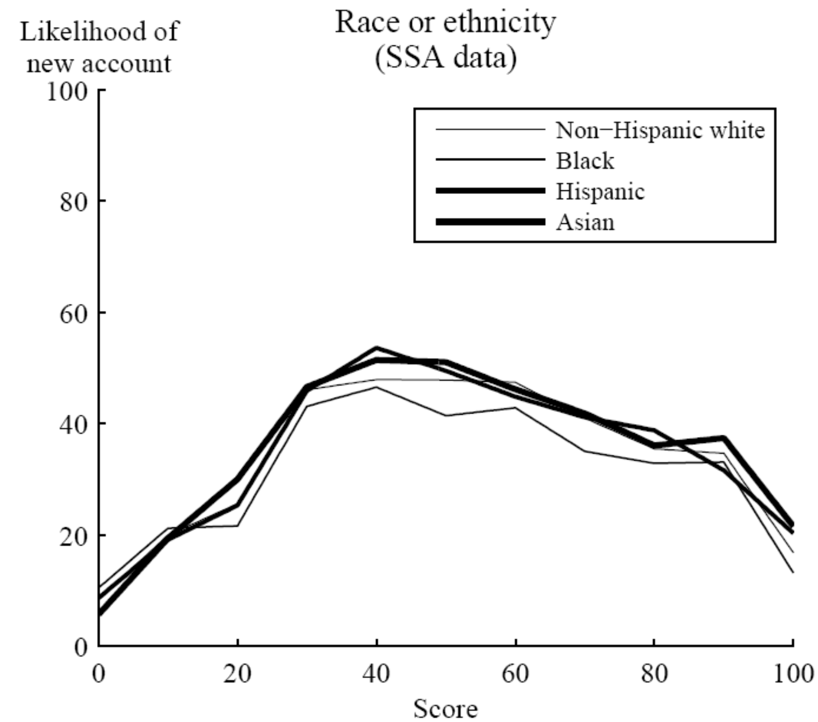

Figure 6. TransRisk Score: Inquiry-Based Proxy for Denials

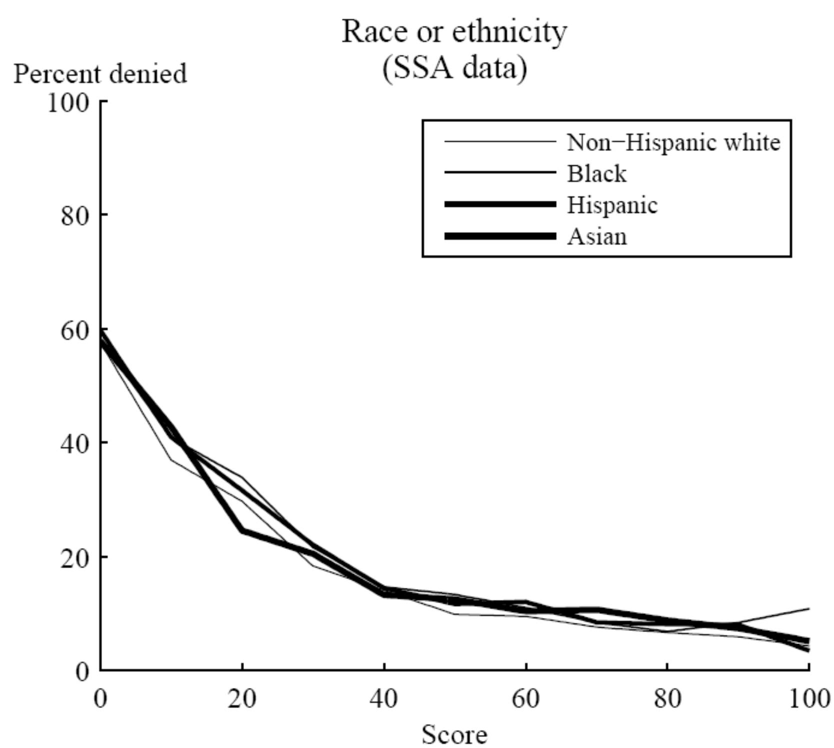

Figure 7.A. TransRisk Score: Mortgage Interest Rate

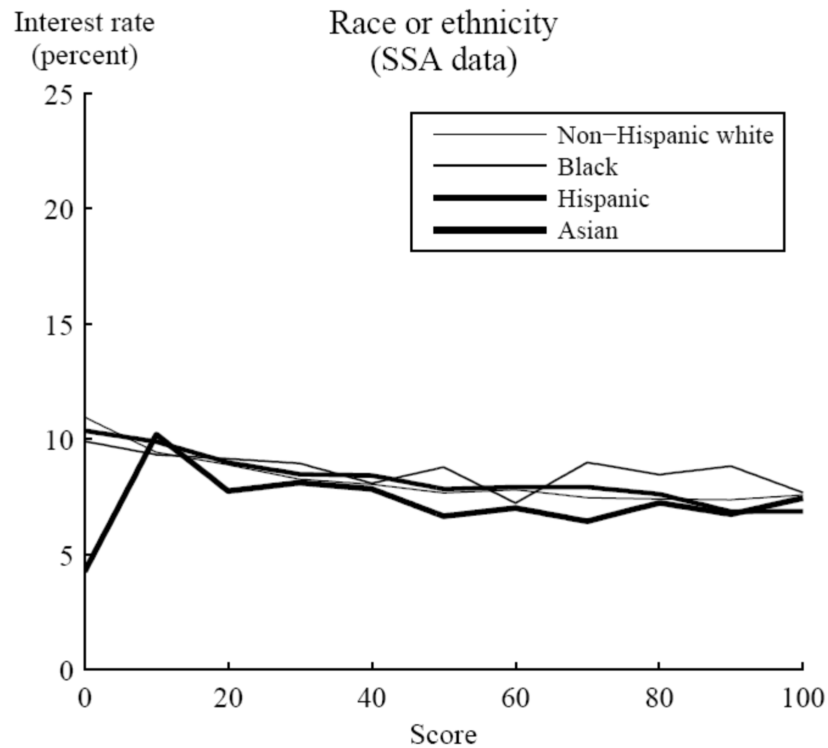

Figure 7.B. TransRisk Score: Auto Loan Interest Rate

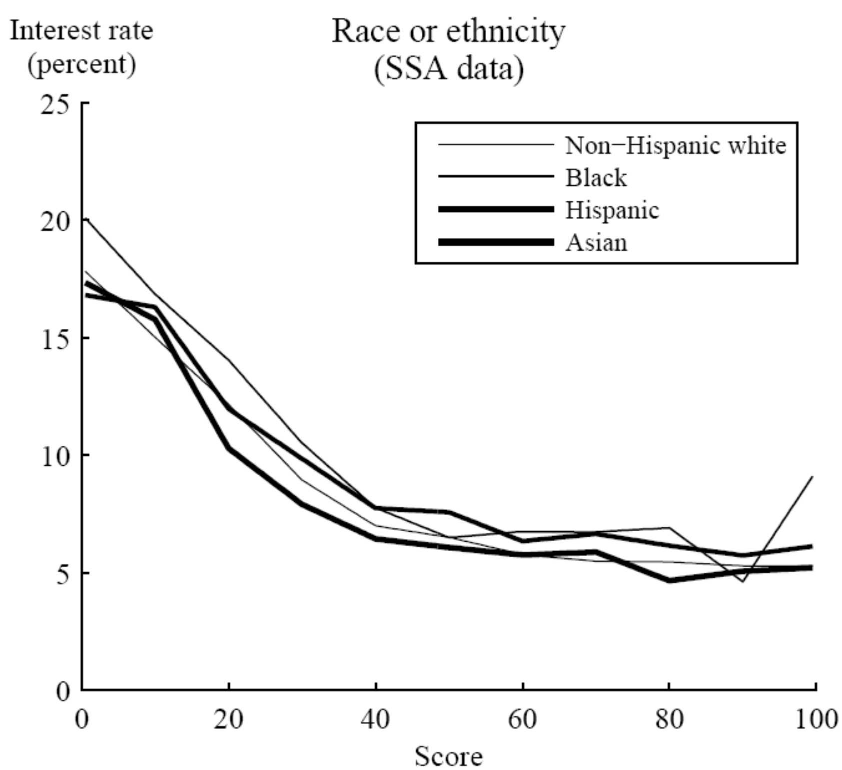

Figure 7.C. TransRisk Score: Other Installment Interest Rate