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THE DEMOGRAPHICS OF LOAN DELINQUENCY: TIPPING POINTS OR TIP OF THE ICEBERG?

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Abstract

Loan-delinquency rates differ sharply across demographic groups. Families that are younger, less-educated and non-white are much more likely to miss payments than older, better-educated and white families. Controlling for a host of observable variables—including differences in balance sheets, family structure and measures of luck such as income shocks—reduces but does not eliminate the ability of some demographic factors to predict missed payments. This result provides only limited support for the view that "demographics don't matter," according to which families with delinquency-prone demographic characteristics miss payments because they simply make riskier choices. These families presumably live closer to the edge financially and more frequently encounter a "tipping point" that pushes them over. An alternative view supported by our data is that systematic forces that include life-cycle effects, socio-economic background, current or historical discrimination and other disadvantage largely shape financial behavior. These structural and systemic factors therefore are important in understanding loan delinquency. Significantly higher delinquency rates among young, less-educated and non-white families may be the "tip of the iceberg" of living with greater financial risk every day.

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Loan-delinquency rates vary significantly across demographic dimensions, including age, education level and race or ethnicity. For example, baseline estimates suggest:

- Families headed by someone under 40 are about 24 percent more likely than families headed by a middle-aged person (ages 40 to 61) to become seriously delinquent—defined as missing at least two consecutive monthly payments within the past year—and about five times as likely as families headed by someone 62 or older;
- Families headed by someone with no more than a high-school diploma are 13 percent more likely to be seriously delinquent at any given time than families headed by someone with a four-year college degree and about two and one half times as likely as families headed by someone with post-graduate education;
- Families headed by an African-American are about 81 percent more likely to be seriously delinquent on a debt than a non-Hispanic white family while Hispanic-headed families (of any race) are about 8 percent more likely to be seriously delinquent than a white family.[1]

Measures of serious delinquency from credit files maintained by the major credit bureaus likewise show stark differences in delinquency rates across demographic categories.[2]

This paper explores the demographic dimensions of household debt and loan delinquency. How different are borrowing levels and delinquency rates across demographic characteristics? Are there other observable household-level variables that predict or explain these differences without reference to demographics? At a deeper level, is it more reasonable to attribute the ultimate cause of demographic differences in delinquency rates to individual choices about risk or to underlying factors over which individuals may have little or no control, such as the riskiness of their financial lives?

We find large differences in rates of loan delinquency across the life cycle, along the educational spectrum and between different racial and ethnic groups. Two types of non-demographic observable variables are moderately successful in predicting individual-level loan delinquency even though these

[1] These figures refer to the relative frequencies of being seriously delinquent based on a logit model applied to the Federal Reserve Board's Survey of Consumer Finances (SCF) during the 1995 to 2013 period. We include all families whether they owe any debt or not; that is, they are unconditional delinquency estimates. These baseline estimates include a constant term and controls for the year in which the survey was conducted but contain no other covariates.

[2] See Federal Reserve Board (2007), Table 17, which covers the period June 2003 to December 2004.

variables are not proxies for demographics themselves. One set consists of information about an individual's credit history and current usage; these variables often are combined to create credit scores, which are highly predictive of delinquency. The variables subsumed in a credit score predict delinquency because individuals' credit performance tends to be persistent; missing payments in the past is highly informative about missing payments in the future.

The second type of information could be termed a household financial audit at a point in time; these variables include financial choices such as the particular assets held and liabilities owed, as well as non-financial characteristics of a family including income shocks, physical health and family structure. The variables uncovered by a financial audit predict delinquency either because they mediate between a family's economic circumstances and its financial outcomes—for example, a high debt load makes delinquency more likely for a given amount of financial stress—or perhaps because they reveal which families are inherently more cautious—for example, maintaining adequate cash reserves may signal prudence more generally—or both.

The question of *why* demographic characteristics predict loan-delinquency rates is more complex. At first glance, one might expect delinquency rates to be roughly equal across demographic categories—that is, young and old, less- and better-educated as well as black, Hispanic, white and Asian borrowers all might cluster around the average delinquency rate of the entire population. This is what we would expect if lenders imposed a single maximum expected-loss threshold on every borrower individually. Any differences in underlying risk by group then would be reflected in different loan-granting rates—that is, more young borrowers would be rejected for loans than old borrowers but, conditional on receiving a loan, the delinquency rates of young and old groups of borrowers would be similar.

Risk-based pricing is an alternative to quantity-based (and constant-risk) rationing of credit. Borrowers who appear riskier *ex ante*—such as young people—might be offered credit just as often as older borrowers but at a higher interest rate (or with other conditions, such as higher down-payment requirements on a mortgage). More young than old borrowers might default but, if the lender charged an appropriate risk premium, the young borrowers who paid back their loans could make young borrowers overall just as profitable as older borrowers as a group.

But why do *ex ante* risky borrowers accept loans with risk-based pricing? Why don't they interpret the high—perhaps punitive—offer price as a signal that they would be better off waiting until their financial strength improves? If a young person, for example, borrows and fails to pay back, her (likely already low) credit score will be damaged further and her financial life will get off to a rocky start. A low credit score also can jeopardize her chance to rent an apartment or get a job. Recovering will not be quick or easy. If, on the other hand, the borrower pays back in full and on time, she will have paid a steep price for credit access—likewise slowing her financial progress.

From the borrower's perspective, therefore, the puzzle of why high loan-delinquency rates are associated with economically weaker demographic groups—young, less-educated, minority individuals and families—boils down to a question of risk. Are families with *ex post* delinquency-prone demographic characteristics more likely to make *ex ante* risky choices in an environment otherwise common to all families? That is, do they choose to "live closer to the edge," making it more likely they will encounter a "tipping point" into delinquency? Or do families we identify *ex post* as possessing delinquency-prone demographic characteristics live in a world with greater *ex ante* risks than families with lower delinquency rates? In this case, individual choices may be constrained. In other words, higher rates of loan delinquency may represent the "tip of the iceberg" that hints at a vastly different and larger set of risks that are hidden from plain view.

Distinguishing between these two perspectives is quite difficult, of course. Our approach is to examine two different empirical models of delinquency. In one—which we call a "tipping-points" model—we assume that all families essentially face the same opportunities and choices. In particular, choices about assets and liabilities, family structure and even the odds of being lucky are the same for everyone. One does not choose one's demographic characteristics but, by assumption of this model, it doesn't matter. If a group of families shows a high delinquency rate it must be—by assumption—that many families in this group simply made riskier choices. We refer to this approach as a "demographics don't matter" model, or DDM, for short. Risky decisions such as borrowing large amounts of money at a high interest rate presumably are the result of individual calculations of risk and return. The implication is that, to improve their financial health, members of groups we identify as high-risk simply need to make better financial decisions—that is, more like those of people with less delinquency-prone demographic characteristics.

An alternative modeling approach recognizes that all or most members of some demographic groups routinely make significantly different choices than members of other groups. For example, the median ratio of debt to assets among young families (headed by someone under 40) in 2007 was 51.0

percent. Among old families (headed by someone 62 or older), the median ratio was 0.1 percent.[3] Clearly, young families as a group were much more exposed to financial risk as the financial crisis and Great Recession unfolded. Did they simply prefer more risk?

The “tipping-points” or DDM framework assigns responsibility for the greater exposure of many young families to their individual decisions to borrow heavily. The alternative “tip-of-the-iceberg” approach—what we call the “peer group matters” or PGM framework—recognizes that young families often face heavy financial obligations, such as paying off student loans and financing big-ticket purchases like cars and a house, before they’ve had time to earn and save very much. It’s also plausible that young families are less financially savvy and experienced than older families and may not understand the risks they are taking as well as their parents and grandparents do. Likewise, less-educated and minority families may be influenced as much or more by their demographically defined peer groups and the circumstances they face than by risk-and-return calculations they perform. These circumstances, in turn, may have been shaped by historical discrimination or other disadvantages, in the case of racial and ethnic minorities, or a radically changed global economy that affects the prospects of people with low levels of education.

To summarize our key results, we use the SCF to document a very strong statistical relationship between a family’s demographic characteristics—including its age, education level and race or ethnicity—and its propensity to become delinquent on a loan. We investigate two measures of delinquency: 1) missing any loan payment within the year prior to the SCF survey (what we term “any delinquency”) and 2) missing at least two consecutive payments in that time period (“serious delinquency”). Young borrowers (under 40), those with at most a high-school education and African-American borrowers are much more likely to be delinquent on either measure than the reference group in each demographic dimension—families headed by someone who was middle-aged (40-61), college-educated or white, respectively. At the same time, older borrowers (62 or more) and people with post-graduate education were much less likely to become delinquent than their respective reference group. Asian families were virtually indistinguishable from white families.

Adopting the “tipping-points” or DDM framework and adding a host of observable covariates to the logit regressions—including controls for the year in which the survey took place, twelve balance-sheet measures, three measures of economically relevant luck and three dimensions of family

[3] See Emmons and Noeth (2015c), Figure 12. The mean ratios of debt to assets in 2007 were 40.0 and 5.3 percent, respectively.

structure— the predictive power of demographic variables for loan delinquency is reduced but not eliminated. Being black continues to predict higher delinquency rates *ceteris paribus* using either definition of delinquency. Being old and possessing a post-graduate degree both significantly reduce the probability of incurring any or a serious delinquency compared to middle-aged and college-educated families, respectively. On the other hand, observable factors that include financial behaviors, family structure and elements of luck or circumstance effectively eliminate the predictive power ofhaving at most a high-school diploma and reverses the effect of being Hispanic. Thus, our results provide only mixed support for the maintained assumption that demographics don't matter. In part, they clearly do—so the tipping-points model of delinquency is not decisively rejected or supported.

The alternative framework we investigate ("tip of the iceberg," which is based on the assumption that peer groups matter) assumes that all families do *not* face the same opportunities and choices and cannot realistically mimic a demographically distant group. Rather, a family's norm may be defined by a demographically similar peer group—in particular, other families of the same age, education and race or ethnicity. To implement this model, we enter all of the explanatory variables in de-meaned form. For example, a particular family's share of assets invested in housing is expressed as the difference between its actual share and its demographically defined peer group's mean share. This reduces the importance for delinquency prediction attributed to individual choice and re-allocates that influence to the age, education and race/ethnicity indicator variables.

The results provide strong support for the peer-group-matters framework or what we termed the "tip of the iceberg" model of delinquency. A family's age, education and race or ethnicity remain highly predictive of any delinquency as well as a serious delinquency even when financial, family-structure and luck or circumstance covariates are included in de-meaned form. This model interprets only the idiosyncratic components of observable variables—for example, the "extra" debt a family owes compared to the average of its peer group—as the family's contribution to its delinquency risk. We assign the predictable or systematic component of those variables (the peer group's average debt, for example) to the peer group's underlying demographic characteristics themselves. We believe this partitioning of the sources of delinquency risk corresponds better to the realities facing most vulnerable families than the facile assumption that every family is entirely free to fashion its own financial circumstances. Simply mimicking the behavior and choices of families with less delinquency-prone demographics may not be possible. The risks facing young and minority families may be due in large part to structural—for example, life-cycle—or historic factors over which they have little or no control.

The paper proceeds as follows. The first section provides basic information on household debt and documents large and persistent differences in loan-delinquency rates across groups of families defined by their demographic characteristics. The second section explores the ability of credit scores to predict delinquency rates without the use of some key demographic information about borrowers. The third section presents results from what we call a ”demographics-don’t-matter” model of delinquency in which unconstrained choices are assumed to make families vulnerable to reaching a tipping point into delinquency. The fourth section describes an alternative delinquency model that assumes choices are constrained—that is, they are not the same for members of every age, education or racial or ethnic group due to structural (or other unobservable) factors. Instead, peer groups represent norms that are themselves associated with demographic factors. The final section concludes.

I. Household Debt and Loan-Delinquency Rates by Demographic Group

Household borrowing differs most by age of family head among the three demographic dimensions we consider. Borrowing activity traces out a hump-shaped pattern along the educational spectrum, first rising and then declining. The debt measure we examine is remarkably similar across racial and ethnic groups. A strong upward trend over time in borrowing intensity is visible in most demographically defined groups.

Household debt by demographic group. Figure 1 shows the median debt-to-assets (DTA) ratio by age of family head over time.[4] Among young families, the 1989 median DTA ratio was 34.5 percent; by 2010, it was 53.0 percent. The ratio dropped back to 45.0 percent in 2013, but remains much higher than in the early years of the SCF. The median DTA ratio increased from 14.3 to 25.8 percent among middle-aged families between 1989 and 2010, declining slightly by 2013. Among old families, the median DTA ratio was zero until 2004, after which it rose to 1.6 percent by 2013.

Differences in median DTA ratios across education levels are greatest between the least educated—high-school drop-outs—and everyone else, as shown in Figure 2. Families headed by someone without a high-school diploma reached a median DTA ratio of only 2.7 percent in 2004 and had dropped back to 0.3 percent by 2013. Among families with high-school education or more, those with no more than a four-year college degree have the highest median DTA ratios at close to 30 percent.

[4] The total dollars of debt owed by each family is divided by the total dollar value of assets owned by that family. The median value of this ratio among all families with a specific demographic characteristic is the group’s median DTA ratio.

Families headed by someone with post-graduate education have lower median DTA ratios than high-school or college families. An increasing trend in median DTA ratios is evident across all education levels throughout most of the sample period.

Racial and ethnic differences in median DTA ratios are remarkably small. Figure 3 shows that the strong upward trend of household indebtedness throughout the last quarter century lifted Latino, Asian and white median DTA ratios from the teens to about 20 percent by 2013. The median DTA ratio of black families rose more than that of any other group, increasing from 4.1 percent in 1989 to 27.6 percent in 2013.

Loan-delinquency rates by demographic group. It should not be surprising that loan-delinquency rates differ significantly by demographic group. As shown below, younger, less-educated and African-American or Latino families generally are more likely to miss payments than their older, better-educated and white or Asian counterparts. Similar patterns are replicated along demographic lines in many other economic and financial measures. Families that are younger, less-educated or non-white experience both higher average unemployment rates and sharper spikes in unemployment during recessions than families that are older, better-educated or white.[5] Younger, less-educated and non-white families generally have significantly lower incomes and wealth than older, better-educated and white families.[6] Demographic characteristics also strongly predict asset and liability holdings, with younger, less-educated and non-white families' balance sheets typically being less liquid, less diversified across asset types and more highly leveraged than their counterparts with the opposite demographic characteristics.[7] Younger, less-educated and non-white families also are less likely to be married or to receive a significant bequest or inheritance. In short, demographics are strongly associated with a host of economic and financial behaviors and outcomes.

Figure 4 shows the share of families that had missed at least two consecutive payments within the year before their SCF interview in each of three age groups.[8] At least one in five young families typically has experienced a recent bout of serious delinquency.[9] At the other extreme, only about five

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[5] See Emmons and Noeth (2013).
[6] See Emmons and Noeth (2015a, 2015b, 2015c).
[7] ibid.
[8] This classification also includes other indicators of serious debt problems such as a bankruptcy or foreclosure.
[9] Note that the figure displays unconditional serious delinquency rates. That is, more than 20 percent of *all* families headed by someone under 40 years old generally have experienced a recent serious delinquency, not merely 20 percent of families with any debt. Conditional serious-delinquency rates are higher because not all families have debt. We prefer the unconditional measure because it captures both a family's decision to take on debt and its ability to service the debt.

percent of families headed by someone 62 or older has experienced a recent serious delinquency; the spike in old families' serious-delinquency rate in 2007 may be due both to the housing crash gathering force at that time and to sampling error. Middle-aged families are intermediate, with 10 to 15 percent of families typically having experienced a serious delinquency within the year before the survey. Thus, age is a strong negative predictor of delinquency—the older the family, the less likely to become delinquent.

Serious-delinquency rates by education level are shown in Figure 5. Families headed by someone with post-graduate education experience the lowest serious-delinquency rates among all education levels. Fewer than one in ten of these families had missed two or more consecutive payments within a year of all SCF survey dates. Between 10 and 15 percent of families with no more than college education typically had experienced a serious delinquency. Among families headed by someone with no more than a high-school diploma, 15 to 20 percent typically have missed two or more consecutive payments at any time. Note that the incidence of serious delinquency is slightly lower among high-school drop-out families than among those headed by high-school graduates. This is due to the lower incidence of debt among high-school drop-outs, not stronger repayment histories.

Figure 6 shows serious-delinquency rates across racial and ethnic groups. Black families experience the highest delinquency rates, with 20 to 30 percent of all families having missed two or more consecutive payments within the year prior to an SCF interview. Latino families experience the next highest delinquency rates, ranging from about 15 to 25 percent. About 10 to 20 percent of white and Asian families experience serious delinquency.

In sum, groups with the highest median DTA ratios—young, less-educated and black or Latino families—typically experience the highest serious-delinquency rates. This broad generalization hides a wealth of subtle detail, however. For example, typical debt burdens and delinquency rates are not monotonic in education level. Debt burdens are more similar across racial and ethnic groups than the corresponding serious delinquency rates are. It is clear that the relationship between demographics, debt and delinquency are complex.

II. Credit Scores and Delinquency Prediction by Demographic Group

Credit-scoring models are important inputs into financial institutions' consumer-lending decisions. This section provides background on credit scores before documenting the demographic dimensions of credit scores and their accuracy in predicting serious delinquencies.

Credit scores. Although skipping a payment can relieve a short-term cash-flow crunch it's likely to be costly because it can lead to late charges or higher borrowing rates. It also may result in losing access to credit altogether for a period of time. Through their effects on credit scores, loan delinquencies also may affect a consumer's access to other services such as banking and insurance, rental housing, utilities, cellphone contracts, government assistance and even employment.

Our assumption throughout this paper is that most people generally understand this trade-off; this is what one might call the "debt bargain." Yet choices about debts—whether to take on a debt obligation, gauging its sustainability and deciding whether payment when due is feasible or desirable—differ systematically across groups. Lenders understand that members of different demographic groups may perceive the debt bargain differently so, to the extent possible, they structure and price their credit offerings accordingly to make every offer of credit potentially profitable.

From the profit-maximizing perspective of lenders, predictable differences in delinquency rates based on potential borrowers' demographic characteristics would suggest conditioning offers of credit on these characteristics. However, it is unlawful under the Equal Credit Opportunities Act (ECOA) for a lender to discriminate against a credit applicant on a prohibited basis in any aspect of a credit transaction.[10] The prohibited bases include race, color, religion, sex, national origin, age and marital status. Under the Fair Housing Act (FHA), the prohibited bases for discrimination in any aspect of a residential real-estate transaction include race, color, religion, sex, national origin, handicap and family status (but not age or marital status).

To avoid violating any law, lenders use credit scores and other underwriting data and judgments that are not based on protected demographic characteristics. Credit-scoring models in common use today rely primarily on five broad types of information about a consumer: (1) payment history, (2) indebtedness, (3) length of credit history, (4) types of credit used, and (5) acquisition of new credit. Lenders supplement credit scores with information provided by the potential borrower at the time of application to underwrite loans.[11] Lender judgment also may be applied if it is not discriminatory in intent or impact. The continued availability and profitability of consumer and mortgage credit testifies to the ability of lenders to overcome the lack of delinquency-relevant demographic information with other underwriting information. The extent to which demographic information retains its predictive power even after incorporating allowable underwriting information generally is unknown by lenders.

[10] Federal Reserve Board (2007), p. O-6.
[11] Ibid, pp. 24-5.

Other groups highly motivated to understand demographic differences in households' credit access and performance include researchers and policymakers. Because publishing research findings does not conflict with the ECOA, the FHA or other anti-discrimination laws, datasets that include demographic identifying factors are in common use by researchers. One example is the Federal Reserve Board's Survey of Consumer Finances (SCF), a detailed triennial snapshot of the financial lives of a representative cross-section of U.S. families. Another is the unique dataset constructed by the Federal Reserve Board in fulfillment of its obligation under the Fair and Accurate Credit Transaction Act of 2003 to study credit scoring. The Board report (Federal Reserve Board, 2007) used data from the Social Security Administration to match credit records of individuals to demographic information such as place and date of birth, race or ethnicity, sex and date of first application for a Social Security card.

Credit scores by demographic group. Even though credit-scoring models do not include demographic information such as education level or race or ethnicity, credit-score distributions correlate strongly with demographic characteristics. The Federal Reserve Board dataset is unusual in its ability to demonstrate these correlations.

Figure 7 displays the credit-score distributions of five age groups as of June 2003.[12] Individuals under 50 are concentrated in the lower half of the overall credit-score distribution while people over 50 tend to have credit scores in the upper half of the distribution. In particular, disproportionate numbers of people under 30 have very low credit scores—18.4 percent rank in the lowest 10 percent (first decile), 15.4 percent rank in the second decile, 14.2 percent rank in the third decile and so on. Among individuals 62 or older, only 2.6 percent rank in the first decile, 4.0 percent in the second decile, 5.2 percent in the third decile and so on. The inflection point is in the 40s or 50s, the credit-score distributions of which are close to the overall distribution. Figure 8 summarizes the information in Figure 7 in cumulative distribution functions (CDFs) for each age group. The CDF for individuals under 30 shows that 75.8 percent rank in the bottom half (first five deciles) of the overall credit-score distribution. Only 24.7 percent of people 62 or older rank in the bottom half of the overall distribution. Fully 40 percent of people 62 or older rank in the top two deciles of the overall distribution while only 1.1 percent of people under 30 rank as high.

Credit-score distributions by race or ethnicity are shown in Figure 9. Almost one third (30.2 percent) of African-Americans rank in the bottom 10 percent (first decile) of the overall credit-score

[12] These are conditional distributions—that is, including only individuals that have a credit score.

distribution. Among Latinos, 15.2 percent are in the first decile. Only 7.6 percent of whites and 5.2 percent of Asians rank in the bottom 10 percent. At the top end of the distribution, only 1.9 percent of blacks and 4.3 percent of Latinos rank in the top decile, while 11.0 percent of Asians and 11.8 percent of whites are in the top 10 percent. Figure 10 shows CDFs by race or ethnicity. Among blacks, 84.9 percent rank in the bottom half (lower five deciles) of the overall credit-score distribution. Just over two-thirds of Latinos (68.8 percent) rank in the bottom half while 42.2 percent of Asians and 44.3 percent of whites are somewhere in the lowest five deciles.

Credit scores also correlate positively with income levels. Income, in turn, generally is associated with education level. Thus, we would expect education to be visible in credit-score rankings.[13]

Delinquency prediction by credit score and demographic characteristic. As noted above, strong correlations between demographic characteristics and loan-delinquency rates are evident in the SCF. This need not indicate that lenders are losing money systematically on borrowers with certain demographic characteristics, however. Credit availability and pricing may vary across these dimensions sufficiently based on legal underwriting methods to make lending viable. Continued access to credit by all demographic groups is evidence that credit pricing and conditions make lending profitable.

The Federal Reserve Board's (2007) unique dataset makes it possible to identify serious-delinquency rates by demographic characteristic and to judge whether missing demographic variables in credit-scoring models are hampering lenders' ability to predict delinquencies. Figure 11 shows the incidence of serious delinquency during an 18-month period by race or ethnicity and age of the borrower.

The differences in loan performance are stark.[14] According to credit-bureau records, about two thirds of black borrowers encountered a serious delinquency during the period while only 18 percent of Asian borrowers experienced serious delinquency. Latinos and whites were intermediate, with 42 and 23 percent missing three or more consecutive payments, respectively. Loan performance also improves

[13] The Federal Reserve Board (2007) reports credit-score distributions by income but that variable is not our focus in this paper so we do not show it here.

[14] The incidence of serious delinquency in the credit-bureau data is noticeably higher than in the SCF survey data for two reasons. First, the credit-bureau data are conditional delinquency rates—that is, calculated only among individuals who have a credit score. The SCF delinquency rates reported above were unconditional, including families that did not have debt (and may not have a credit score). Second, it is plausible that many people under-report their credit difficulties in surveys while credit-bureau records may be more accurate. Factors that could go in the opposite direction include mistakes or duplications in the credit-bureau records.

markedly with a borrower's age. While 44 percent of borrowers under 30 experienced serious delinquency during the 18-month sample period, only 12 percent of borrowers 62 or older did so.

How well did credit scores anticipate loan performance—and specifically, along demographic lines? Figure 12 reports the results of the Federal Reserve Board's prediction exercise using generic credit-scoring models from credit bureaus and a credit-scoring model the authors developed for the purposes of the report. Scores were computed as of June 2003; delinquency was measured during the subsequent 18 months.

Age-based delinquency predictions were quite good. For example, the actual rate of serious delinquency during the 18-month period was almost identical to the predicted delinquency rate (difference of -0.03 percentage points) for borrowers aged 30-39 in June 2003. This is not too surprising, however, because age is highly correlated with variables in all credit-scoring models related to the length of a borrower's credit history. In other words, it is not difficult for lenders to predict a borrower's age and condition their credit offers on that variable.

Prediction errors along racial and ethnic lines are more striking. Black borrowers encountered serious delinquencies at a rate of 5.4 percentage points higher than predicted; Latino borrowers were seriously delinquent 1.7 percentage points more often than predicted. White borrowers were delinquent 0.8 percentage points less than predicted while Asian borrowers outperformed the model predictions by 1.9 percentage points.

Clearly, lenders would consider adding race or ethnicity to their credit-scoring models if this were not a protected category. The effects likely would be to raise credit scores of white and Asian borrowers (and possibly lower the interest rates offered) while lowering credit scores of Latino and black borrowers (and raising the interest rates offered). Said differently, credit apparently was "underpriced" to black and Latino borrowers during the study period and was "overpriced" to white and Asian borrowers.

III. A Demographics-Don't-Matter (DDM) Model of Delinquency: "Tipping Points"

The simplest approach to modeling loan delinquency empirically is to assume that all borrowers are essentially the same except as indicated by observable variables. To determine if demographic factors are important, we include in a series of logit models a set of indicator variables for age of the family head in three broad ranges; highest education level of the family head in three categories; and four race or ethnicity classifications of the survey respondent. The logit models produce odds ratios, expressing the predicted delinquency probability for a family with a given demographic characteristic relative to that of a reference group. We use middle-aged (40-61 years old), four-year college-educated and non-Hispanic white families as reference groups for age, education and race or ethnicity, respectively. The other groups are young (under 40) and old (62 or over); high school or less and post-graduate education; and African-American, Hispanic and other, which is mostly Asian.

If the non-demographic variables explain all of the variation in loan performance—i.e., if demographics don't matter—the estimated odds ratios on the demographic indicator variables will be close to one and statistically insignificant. If this is not true—i.e., if odds ratios are statistically significantly different than one—we conclude that something related to the demographic characteristic in question is important for determining loan performance. The true cause could be unobservable and could relate to life-cycle effects, changing economic opportunities for different skill levels, current or historical discrimination or a host of other deep-seated factors somehow related to demographics. We return to these factors in the next section.

Using the Survey of Consumer Finances during 1995-2013, we have 34,479 observations of families each with a rich set of demographic identifiers along with detailed information on balance sheets and other financial matters, as well as non-financial information on income, inheritance, self-assessed health status, marital status, number of children, provision of support to extended family and many other variables. The main sets of non-demographic independent variables we include are 1) indicator variables for survey year; 2) twelve variables measuring the presence and asset shares of various assets and liabilities; 3) three variables that measure "luck," including experiencing a negative income shock in past year, receipt of an inheritance, and self-assessed health status; and 4) three measures of family structure, including marital or cohabitation status, number of children in the household, and whether the family provides financial support to extended family. We investigate two measures of delinquency: 1) any missed payment within the year prior to the SCF interview (any delinquency), and 2) at least two consecutive missed monthly payments within the last year (serious delinquency). Table 1, panel A, explains the variables used in our empirical models reported in this section.

The results of estimating logit models of delinquency using SCF data under the DDM assumption are reported in Table 2. Panel A includes results for models using any delinquency as the dependent variable; panel B includes results using serious delinquency as the dependent variable. The results are qualitatively similar. Our overall conclusion is that there is mixed support for the demographics-don't-matter hypothesis. In some respects, demographics certainly do matter for loan delinquency even when controlling for many observable behaviors and circumstances.

The "raw" delinquency predictions—including demographic indicators alone—are in Column 1 of Table 2, panels A and B, respectively. Column 2 adds indicator variables for the year in which the SCF interview of each family took place; we use this as our baseline specification.

With the exception of families in the "other" racial or ethnic group, which comprises mostly Asian families, and serious delinquency among Hispanic families, all of the age, education and race or ethnicity categories are highly significant differentiators of the risk of both any delinquency (panel A) and serious delinquency (panel B). In particular, young families are 29 (24) percent more likely than middle-aged families to become delinquent (seriously delinquent); while old families are 69 (73) percent less likely to be delinquent (seriously delinquent) than middle-aged families.

Likewise, families headed by someone with no more than a high-school diploma are 9 (13) percent more likely to be delinquent (seriously delinquent) than a family headed by someone with at least some college but no more than a four-year college degree. Those college-educated families, in turn, are 48 (54) percent more likely to be delinquent (seriously delinquent) than families with post-graduate education. Finally, black families are 75 (81) percent more likely to become delinquent (seriously delinquent) than white families; Hispanic families are 13 (8) percent more likely to be delinquent (seriously delinquent), although the latter results aren't statistically significant. Other (mostly Asian) families' loan performance is statistically indistinguishable from that of whites.

Adding the full set of balance-sheet variables (column 3) exerts a noticeable impact on several odds ratios. The most dramatic effect is visible for young families. Including financial covariates transforms their predicted delinquency risk from 24 percent greater than middle-aged families to as much as 20 percent less (under the serious-delinquency criterion). In other words, the reason young families are at greater risk of delinquency than middle-aged families is because they have riskier balance sheets.

As shown in Figure 1, young families have significantly higher debt-to-assets ratios than middle-aged families. They also have less liquidity and asset diversification. These and other age-related balance-sheet differences plausibly are caused at least in part by life-cycle demands and circumstances. Once these are taken into account, young families actually are *less* risky than middle-aged families!

Of course, a young family cannot choose simply to fashion a balance sheet identical to those of middle-aged families. Indeed, this is precisely the point of the alternative modeling approach we describe below. Balance-sheet differences may "explain" the higher delinquency risk of a typical young family but there may be little that a young family realistically can do about it. So the explanation may be a moot point. Likewise, families with very low levels of education or those who are non-white cannot transform themselves into their respective reference groups.

Including financial variables also reduces the predicted risk differences between middle-aged and old families as well as between Hispanic and white families. In the latter case, Hispanic families become virtually indistinguishable from white families when differences in balance sheets are taken into account. Predicted delinquency risk of black families relative to white families declines slightly when financial variables are included and statistical significance declines notably for families with at most a high-school diploma for both delinquency outcomes. Post-grad families' predicted delinquency risk becomes more similar to that of college grads but remains statistically much lower.

Columns 4 and 5 of each panel add variables designed to capture luck and family structure, respectively. Compared to the model in Column 2, those including luck and family structure variables demonstrate only marginal effects of the included variables—albeit enough to reduce or eliminate the statistical significance of two demographic categories. In particular, taking into account income shocks, inheritances and health status, families with no more than a high-school diploma become indistinguishable from their reference group on both delinquency measures. Including family structure eliminates differences between Hispanic and white families for any delinquency while the coefficient was already statistically insignificant for serious delinquency.

Column 6 reports results from a model that includes all of the independent variables discussed so far. When we use any delinquency as the dependent variable (panel A), four of the six demographic groups that were significantly different than their reference groups in the baseline specification—young, old, graduate degree and black—retain their significance. When predicting serious delinquency (panel B), those four categories retain their significance while young and Hispanic families switch from being riskier than middle-aged and white families in the baseline to being less risky in the full model.

Comparing the sequence of models examined in both panels of Table 2, balance-sheet measures as a group clearly are the most important observable variables we consider in reducing the predictive power of (some) demographic characteristics. Within the set of balance-sheet variables (see Table 1), the measures that are statistically significant in predicting any delinquency are:

- Indicator for durable-goods ownership (positively associated with delinquency risk)
- Indicator for maintaining at least one week's income worth of safe and liquid assets (negatively associated with delinquency risk)
- Indicator for homeownership (negative)

- Indicator for owing non-mortgage debt (strongly positive)
- Indicator for owing mortgage debt (negative)
- Value of housing owned relative to total assets (positive)
- Value of financial and business assets owned relative to total assets (positive)
- Value of non-mortgage debt owed relative to total assets (positive)
- Value of mortgage debt owed relative to total assets (positive)

Other observable variables that are statistically important in predicting any delinquency are:

- Negative income shock (positive—i.e., lower than usual income increases delinquency risk)
- Receipt of bequest or gift (positive)
- Good health (negative)
- Married or cohabiting (negative)
- Number of children (positive)
- Provide support to extended family (positive)

The signs and statistical significance of non-demographic covariates were the same when predicting serious delinquency except that durable-goods ownership, mortgage debt ownership, and marital status were insignificant.

Overall, we interpret these results as providing only limited evidence in favor of the framework that asserts demographics don't matter. The demographic characteristics that cannot be "explained away" by adding observable covariates to a logit model of delinquency risk are being old or young, having a post-graduate degree and being African-American. The first three are robust predictors of low delinquency risk while the fourth is a robust predictor of high delinquency risk. Conversely, the higher baseline delinquency risk of families with at most a high-school diploma and Latino families disappears when other variables are added. Young families are unusual in that their baseline risk is significantly above their middle-aged reference group but they appear to be less risky when observable behaviors and characteristics are added.

IV. A Peer-Groups-Matter (PGM) Structural-Determinants Model of Loan Delinquency: Tip of the Iceberg

We recognize potentially important differences in access to opportunity, risks faced and the range of viable choices facing members of different age, education and racial or ethnic groups by transforming the observable independent variables into deviation form. That is, the adjusted value of a variable is its observed value minus the peer-group mean, where the peer group is defined as families of the same race or ethnicity with similar education in the same life-cycle stage.[15] See Part B of Table 1 for variable definitions. The elevated delinquency rates we observe for some demographically defined groups may be just the "tip of the iceberg" of elevated risks those families face.

The result of using variables in deviation form is that only idiosyncratic variation in balance-sheet choices, luck or family structure contribute to the model's explanation of delinquency risk that is not ultimately related to demographic characteristics. Systematic (predictable) differences across families therefore are absorbed into the age, education or race and ethnicity indicator variables by construction. Because there are, in fact, sizable differences in peer-group means for a number of the independent variables we use, the importance assigned to unobservable forces linked to age, education and/or race and ethnicity in the peer-groups-matter (PGM) framework necessarily will be greater than in the demographics-don't-matter (DDM) framing.

The results of estimating logit models of delinquency using SCF data under the PGM assumption are reported in Table 3. As before, panel A includes results for models using any delinquency as the dependent variable; panel B includes results using serious delinquency as the dependent variable. Even more so than under the DDM assumption, the choice of dependent variable matters little qualitatively.

The "raw" delinquency predictions—including demographic indicators alone—in Column 1 of Table 3, panels A and B, are identical to those reported in Table 2; likewise, what we term baseline results in column 2 are identical in Tables 2 and 3.

In stark contrast to the results in the previous section, adding the full set of de-meaned balance-sheet variables (column 3) in the PGM framework has virtually no effect on the odds ratios reflecting relative delinquency risks. This suggests that virtually all of the important differences in balance-sheet variables across families are systematic, i.e., fundamentally connected to their underlying demographic characteristics. For example, one young family's debt-to-assets ratio may differ from that of another young family, but in many cases this difference would be swamped by the differences between the averages of young peer groups and those of middle-aged and especially old peer groups. In other words,

[15] Due to sample-size limitations, we condense racial and ethnic groups from four to two and education groups from three to two to create 12 peer groups (rather than the 36 potential combinations implied by our regression specifications). The two racial/ ethnic categories are (1) Non-Hispanic white or other/Asian, (2) Non-Hispanic African-American/black or Hispanic, any race. The two education categories are (1) High school or GED diploma and below, (2) Some college or any college up to graduate/professional degree. The three age categories are (1) Young, headed by someone under 40; (2) Middle-aged, headed by someone between 40 and 61; (3) Old, headed by someone 62 years old or older. The result is 12 peer groups, to one of which each family is assigned.

the systematic life-cycle determinants of debt burdens would dominate idiosyncratic behavioral differences.

Compared to the model in Column 2, differences in odds ratios reported in columns 4 and 5 including luck and family-structure variables are almost invisible. This suggests idiosyncratic variation is of little consequence. For example, systematic differences in inheritances—say, between peer groups representing highly educated whites and those containing less-educated blacks and Latinos—typically are much larger than idiosyncratic differences within either type of peer group (essentially, rich vs. poor groups).

Column 6 in both panels A and B reports results from a model that includes all of the independent observable variables. Not surprisingly, the odds ratios in both panels' column 6 are quite similar to those in column 2 (as well as in columns 3, 4 and 5). Interestingly, many of the implied differences in delinquency risk between individual demographic groups and their reference group—for example, between young and middle-aged families—are greater in the full model than in the baseline. This suggests that the idiosyncratic choices and circumstances of individual families tend to increase their delinquency risk; in other words, after taking into account systematic age-related forces, young families' choices compound their riskiness. These effects are small, however. The dominant influence on delinquency risk remains demographically determined factors.

We interpret the results in this section as strong evidence in favor of a peer-groups-matter framework—and therefore, demographics matter. Age, education and race or ethnicity are very important determinants of delinquency risk even after controlling for observable idiosyncratic mediating influences such as balance-sheet choices, income shocks, health and family structure.

V. Conclusions

Demographic characteristics including age, education and race or ethnicity are correlated with a host of economic and financial behaviors and outcomes including borrowing and delinquency rates. If demographic factors truly didn't matter—if all individuals and families faced identical choices and opportunities in what we called a Demographics-Don't-Matter framework—then these correlations simply might reflect a connection between differences in risk preferences and differences in age, education and race or ethnicity. Groups that more frequently miss loan payments, for example, might just prefer "living close to the edge" financially so that a given economic or financial shock is more likely to represent a tipping point into delinquency. In principle, any member of a delinquency-prone demographic group could mimic the behavior of families that aren't as likely to be delinquent; most simply choose not to do so.

An alternative approach to understanding demographic correlations with delinquency rates is to assume that all groups do *not* face identical choices and opportunities. Instead, for structural or historical reasons, some individuals and families may live with more risk than others. Young people, for example, may face greater immediate financial challenges with higher stakes than do older people; those with low levels of education may face fewer economic opportunities than those with high skills; and black and Latino families may start their financial lives at an inherent disadvantage. To proxy for these structural or systemic factors, we partition observable financial and non-financial choices and behaviors into peer-group effects and individual choices relative to those peer-group means. This is a Peer-Groups-Matter framework.

Using Survey of Consumer Finances data for the period 1995-2013, we find mixed support for the DDM hypothesis. In other words, even if we assume that all families face the same opportunities and choices then differences in a large set of observable financial and non-financial variables only partially eliminate the role of demographic characteristics in predicting loan delinquency. Under this theoretical framework, groups with high delinquency risks have chosen to take on more risk; they could, if they chose, mimic low-risk groups and eliminate the gap in delinquency rates.

When we partition the potential explanatory variables into peer-group and idiosyncratic parts, we find strong support for a PGM hypothesis. Even after controlling for idiosyncratic choices of assets and liabilities, family structure and propensities to be lucky, a family's stage of life, its education and its race or ethnicity remain highly significant predictors of delinquency. Delinquency-prone demographic groups may face greater risk for structural or systemic reasons rather than simply having a taste for more risk.

The implications for research and policy are clear. The DDM framework that dominates research and most credit-market policies receives limited empirical support. Even controlling for "good vs. bad choices and behavior," being old or highly educated is an advantage in avoiding delinquency; being black is a disadvantage. The PGM framework that recognizes inherent differences in exposure to risk is strongly supported. Age, education and race matter; individual choices and behavior may not be enough to overcome them. Research and policy that ignore these results subject some demographic groups to greater risk even while "blaming the victim." Future research and policy could usefully explore how framing of choice and opportunity affect our conclusions about how credit and other markets actually do and should operate.

References

Emmons, William R. and Noeth, Bryan J. "Economically Vulnerable and Financially Fragile," *Review*, Federal Reserve Bank of St. Louis, Sept.-Oct. 2013.

Emmons, William R. and Noeth, Bryan J. "Race, Ethnicity and Wealth," in *The Demographics of Wealth*, Federal Reserve Bank of St. Louis, Feb. 2015a.

Emmons, William R. and Noeth, Bryan J. "Education and Wealth," in *The Demographics of Wealth*, Federal Reserve Bank of St. Louis, April 2015b.

Emmons, William R. and Noeth, Bryan J. "Age, Birth Year and Wealth," in *The Demographics of Wealth*, Federal Reserve Bank of St. Louis, July 2015c.

Federal Reserve System, Board of Governors, *Report to the Congress on Credit Scoring and Its Effect on the Availability and Affordability of Credit*, Submitted to the Congress pursuant to section 215 of the Fair and Accurate Credit Transactions Act of 2003, August 2007.

Table 1: Variable definitions

A. Tipping-points or "demographics don't matter" (DDM) Models		
Categories and variables	**Type of variable**	**Notes**
Any delinquency		
Late payments sometime in the last year	0 or 1	Yes equals 1, no equals 0
Serious delinquency		
Payments were late for at least 60 days sometime in the past year	0 or 1	Yes equals 1, no equals 0
Race or ethnicity of the family head		
Non-Hispanic African-American or black	0 or 1	Exactly one race or ethnicity for each family
Hispanic/Latino, any race	0 or 1	Self-reported in survey
Non-Hispanic white	Omitted from the regressions	If more than one indicated, use the first one mentioned
Other	0 or 1	
Age group		Exactly one age group for each family
Young	0 or 1	Under 40 equals 1
Middle-aged	Omitted from regressions	
Old	0 or 1	62 or older equals 1
Survey year		
1998, 2001…, 2013	1 if survey responses in this year; 0 otherwise	
1995	Omitted from regressions	
Highest level of education of the family head		
High-school diploma or G.E.D. or less	0 or 1	Exactly one education level for each family
No more than a 4-year college degree	Omitted from regressions	
Professional or graduate degree	0 or 1	
Family structure		
Married	0 or 1	1 if married or cohabiting
Number of children	0, 1, 2,…	
Provides support to extended family	0 or 1	Support paid by family > 0.
Financial behavior		
Owner of durable goods	0 or 1	Cut-off value: 1/52 of "usual" family income or 1,000 2013 USD.
Share of total assets represented by the value of durable goods owned	Percent, between 0 and	

	100	
Owner of residential real estate	0 or 1	Cut-off value: 1/52 of "usual" family income or 1,000 2013 USD.
Share of total assets represented by the value of residential real estate owned	Percent, between 0 and 100	
Owner of financial and business assets	0 or 1	Cut-off value: 1/52 of "usual" family income or 1,000 2013 USD.
Share of total assets represented by the value of financial and business assets owned	Percent, between 0 and 100	
Owes some kind of non-mortgage debt	0 or 1	Cut-off value: 1/52 of "usual" family income or 1,000 2013 USD.
Share of total assets represented by the value of non-mortgage debt owed	Percent, 0 or greater	
Owes some kind of mortgage (home-secured) debt	0 or 1	Cut-off value: 1/52 of "usual" family income or 1,000 2013 USD.
Share of total assets represented by the value of mortgage debt owed	Percent, 0 or greater	
Luck		
Income was lower than usual (Negative income shock)	0 or 1	Family head responded "Income was unusually low compared to what you would expect in a "normal" year."
Received a bequest	0 or 1	Cut-off value: 1/52 of "usual" family income or 1,000 2013 USD.
Health status	0 or 1	Self-reported health of family head, coded 0 if poor or satisfactory, 1 if good or excellent

B. Tip-of the-iceberg models based on peer-group means (PGM)

Peer Group Definitions: Due to sample-size limitations, we combine racial and ethnic groups and education groups to create 12 peer groups. We define two racial/ethnic categories: (1) Non-Hispanic white or other/Asian, (2) Non-Hispanic African-American/black or Hispanic, any race. We define two education categories: (1) High school or GED diploma and below, (2) Some college or any college up to graduate/professional degree. We define three age categories: (1) Young, headed by someone under 40; (2) Middle-aged, headed by someone between 40 and 61; (3) Old, headed by someone 62 years old or older. The result is 12 peer groups, with each family assigned to one of them.

Categories and variables	Type of variable	Notes
Loan delinquency		
Same as above.		
Race or ethnicity of the family head		
Same as above.		
Age groups		
Same as above.		
Survey year		
Same as above.		

Highest level of education of the family head		
Same as above.		
Family structure		
Adjusted marital status	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted number of children	Continuous on [-10, 10]	Number of children minus mean of peer group, 0 minus mean of peer group otherwise.
Adjusted indicator for provision of support to extended family	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Financial behavior		
Adjusted owner of durable goods	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted share of total assets represented by the value of durable goods owned	Continuous on [-100, 100].	Actual share minus mean of peer group.
Adjusted owner of residential real estate	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted share of total assets represented by the value of residential real estate owned	Continuous on [-100, 100].	Actual share minus mean of peer group.
Adjusted owner of financial and business assets	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted share of total assets represented by the value of financial and business assets owned	Continuous on [-100, 100].	Actual share minus mean of peer group.
Adjusted owing of some kind of non-mortgage debt	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted share of total assets represented by the value of non-mortgage debt owed	Continuous on [-100, 100].	Actual share minus mean of peer group.
Adjusted owing of some kind of mortgage (home-secured) debt	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted share of total assets represented by the value of mortgage debt owed	Continuous on [-100, 100].	Actual share minus mean of peer group.
Luck		
Adjusted negative income shock.	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted receipt of a bequest	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.
Adjusted health status	Continuous on [-1, 1]	1 minus mean of peer group; 0 minus mean of peer group otherwise.

Table 2 Odds Ratios from Logit Models of Delinquency: DDM Models

A) Dependent variable: Late payment sometime within the last year

The framework is "demographics don't matter" (DDM), in which the behavioral variables are entered as observed. The assumption is that these variables are not meaningfully correlated with the age, education or race variables. Omitted categories are: Middle-aged (ages 40-61); College (education more than high-school diploma but not more than 4-year college degree); and White (non-Hispanic white family head).

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	0.21*** (0.00)	0.20*** (0.00)	0.09*** (0.00)	0.23*** (0.00)	0.19*** (0.00)	0.08*** (0.00)
Young (under 40)	1.28*** (0.00)	1.29*** (0.00)	0.89*** (0.00)	1.33*** (0.00)	1.27*** (0.00)	0.92*** (0.01)
Old (62 or older)	0.31*** (0.00)	0.31*** (0.00)	0.51*** (0.00)	0.30*** (0.00)	0.35*** (0.00)	0.57*** (0.00)
High-school diploma or less	1.09** (0.02)	1.09*** (0.01)	1.07* (0.06)	1.03 (0.36)	1.07** (0.03)	1.05 (0.15)
More than 4-year college degree	0.52*** (0.00)	0.52*** (0.00)	0.68*** (0.00)	0.55*** (0.00)	0.52*** (0.00)	0.68*** (0.00)
Black	1.75*** (0.00)	1.75*** (0.00)	1.52*** (0.00)	1.69*** (0.00)	1.61*** (0.00)	1.46*** (0.00)
Hispanic	1.14*** (0.01)	1.13** (0.02)	1.05 (0.28)	1.09* (0.08)	1.04 (0.47)	0.99 (0.87)
Other (Asian)	1.01 (0.88)	1.00 (0.99)	1.01 (0.90)	0.96 (0.65)	0.97 (0.70)	0.98 (0.78)
Survey year		Yes	Yes	Yes	Yes	Yes
Balance sheet			Yes			Yes
Luck				Yes		Yes
Family structure					Yes	Yes

NOTE: p-value statistics are in parentheses; * denotes significance at ≤ 10%, ** denotes ≤ 5%, *** denotes ≤ 1%. An asterisk indicates the block of variables was included in the logit regression. See Table 1 for variable details. Data are from the Survey of Consumer Finances, comprising nine triennial waves between 1995 and 2013. Total observations are 34,479, on average, over the five implicates used in each regression. Standard errors are bootstrapped with 999 replications and are adjusted for imputation uncertainty. Sample weights are used in regressions.

B) Dependent variable: Payments were late for at least 60 days sometime in the last year

The framework is "demographics don't matter" (DDM), in which the behavioral variables are entered as observed. The assumption is that these variables are not meaningfully correlated with the age, education or race variables. Omitted categories are: Middle-aged (ages 40-61); College (education more than high-school diploma but not more than 4-year college degree); and White (non-Hispanic white family head).

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	0.07*** (0.00)	0.06*** (0.00)	0.03*** (0.00)	0.08*** (0.00)	0.06*** (0.00)	0.03*** (0.00)
Young (under 40)	1.21*** (0.00)	1.24*** (0.00)	0.80*** (0.00)	1.31*** (0.00)	1.20*** (0.00)	0.87*** (0.00)
Old (62 or older)	0.27*** (0.00)	0.27*** (0.00)	0.50*** (0.00)	0.27*** (0.00)	0.30*** (0.00)	0.55*** (0.00)
High-school diploma or less	1.11* (0.07)	1.13** (0.04)	1.04 (0.54)	1.00 (0.97)	1.12* (0.06)	0.99 (0.89)
More than 4-year college degree	0.46*** (0.00)	0.46*** (0.00)	0.66*** (0.00)	0.52*** (0.00)	0.46*** (0.00)	0.67*** (0.00)
Black	1.83*** (0.00)	1.81*** (0.00)	1.36*** (0.00)	1.67*** (0.00)	1.60*** (0.00)	1.31*** (0.00)
Hispanic	1.12 (0.15)	1.08 (0.35)	0.93 (0.35)	0.99 (0.93)	0.98 (0.77)	0.86** (0.03)
Other (Asian)	0.94 (0.67)	0.92 (0.55)	0.88 (0.40)	0.84 (0.19)	0.88 (0.37)	0.82 (0.16)
Survey year		Yes	Yes	Yes	Yes	Yes
Balance sheet			Yes			Yes
Luck				Yes		Yes
Family structure					Yes	Yes

NOTE: p-value statistics are in parentheses; * denotes significance at ≤ 10%, ** denotes ≤ 5%, *** denotes ≤ 1%. An asterisk indicates the block of variables was included in the logit regression. See Table 1 for variable details. Data are from the Survey of Consumer Finances, comprising nine triennial waves between 1995 and 2013. Total observations are 34,479, on average, over the five implicates used in each regression. Standard errors are bootstrapped with 999 replications and are adjusted for imputation uncertainty. Sample weights are used in regressions.

Table 3 Odds Ratios from Logit Models of Delinquency: PGM Models

A) Dependent variable: Late payment sometime within the last year

The framework is "peer groups matter" (PGM), in which the behavioral variables are de-meaned based on peer groups. See peer group definition in Table 1B. Omitted categories are: Middle-aged (ages 40-61); College (education more than high-school diploma but not more than 4-year college degree); and White (non-Hispanic white family head).

Column	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.21*** (0.00)	0.20*** (0.00)	0.15*** (0.00)	0.19*** (0.00)	0.20*** (0.00)	0.14*** (0.00)
Young (under 40)	1.28*** (0.00)	1.29*** (0.00)	1.34*** (0.00)	1.30*** (0.00)	1.29*** (0.00)	1.36*** (0.00)
Old (62 or older)	0.31*** (0.00)	0.31*** (0.00)	0.28*** (0.00)	0.31*** (0.00)	0.31*** (0.00)	0.28*** (0.00)
High-school diploma or less	1.09** (0.02)	1.09*** (0.01)	1.14*** (0.00)	1.10*** (0.01)	1.09*** (0.01)	1.14*** (0.00)
More than 4-year college degree	0.52*** (0.00)	0.52*** (0.00)	0.66*** (0.00)	0.55*** (0.00)	0.52*** (0.00)	0.66*** (0.00)
Black	1.75*** (0.00)	1.75*** (0.00)	1.88*** (0.00)	1.76*** (0.00)	1.75*** (0.00)	1.89*** (0.00)
Hispanic	1.14*** (0.01)	1.13** (0.02)	1.18*** (0.00)	1.13*** (0.01)	1.13** (0.02)	1.18*** (0.00)
Other (Asian)	1.01 (0.88)	1.00 (0.99)	1.00 (0.99)	0.96 (0.66)	0.97 (0.68)	0.97 (0.70)
Survey year		Yes	Yes	Yes	Yes	Yes
Balance sheet			Yes			Yes
Luck				Yes		Yes
Family structure					Yes	Yes

NOTE: p-value statistics are in parentheses; * denotes significance at ≤ 10%, ** denotes ≤ 5%, *** denotes ≤ 1%. An asterisk indicates the block of variables was included in the logit regression. See Table 1 for variable details. Data are from the Survey of Consumer Finances, comprising nine triennial waves between 1995 and 2013. Total observations are 34,479, on average, over the five implicates used in each regression. Standard errors are bootstrapped with 999 replications and are adjusted for imputation uncertainty. Sample weights are used in regressions.

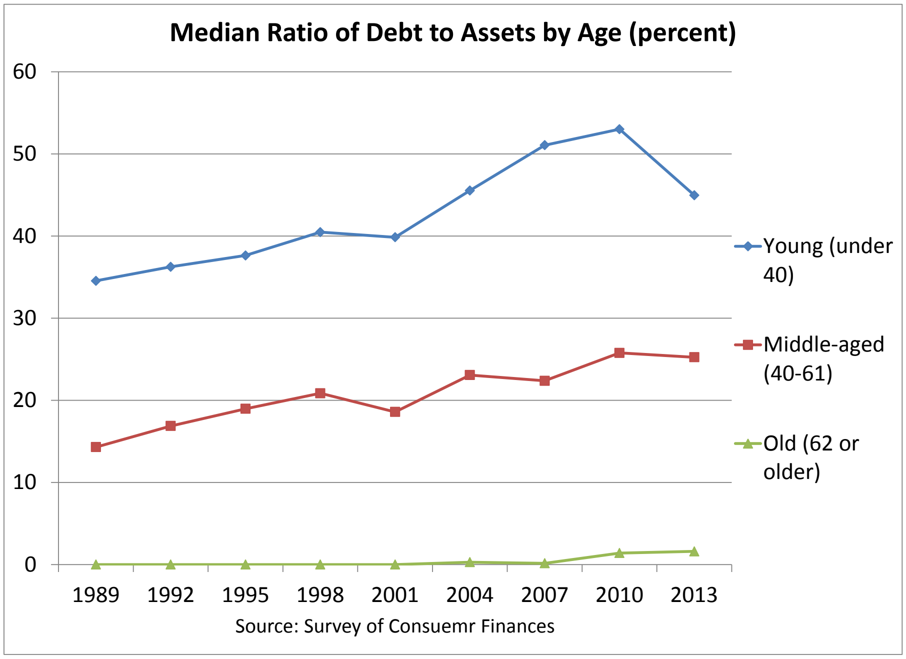
B) Dependent variable: Payments were late for at least 60 days sometime in the last year

The framework is "peer groups matter" (PGM), in which the behavioral variables are de-meaned based on peer groups. See peer group definition in Table 1B.Omitted categories are: Middle-aged (ages 40-61); College (education more than high-school diploma but not more than 4-year college degree); and White (non-Hispanic white family head).

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Constant	0.07*** (0.00)	0.06*** (0.00)	0.03*** (0.00)	0.05*** (0.00)	0.06*** (0.00)	0.03*** (0.00)
Young (under 40)	1.21*** (0.00)	1.24*** (0.00)	1.30*** (0.00)	1.26*** (0.00)	1.23*** (0.00)	1.35*** (0.00)
Old (62 or older)	0.27*** (0.00)	0.27*** (0.00)	0.25*** (0.00)	0.27*** (0.00)	0.27*** (0.00)	0.25*** (0.00)
High-school diploma or less	1.11* (0.07)	1.13** (0.04)	1.19*** (0.01)	1.14** (0.03)	1.13** (0.04)	1.19*** (0.01)
More than 4-year college degree	0.46*** (0.00)	0.46*** (0.00)	0.63*** (0.00)	0.52*** (0.00)	0.46*** (0.00)	0.65*** (0.00)
Black	1.83*** (0.00)	1.81*** (0.00)	1.86*** (0.00)	1.82*** (0.00)	1.77*** (0.00)	1.91*** (0.00)
Hispanic	1.12 (0.15)	1.08 (0.35)	1.16* (0.06)	1.08 (0.36)	1.09 (0.27)	1.14* (0.09)
Other (Asian)	0.94 (0.67)	0.92 (0.55)	0.86 (0.33)	0.84 (0.20)	0.88 (0.37)	0.81 (0.13)
Survey year		Yes	Yes	Yes	Yes	Yes
Balance sheet			Yes			Yes
Luck				Yes		Yes
Family structure					Yes	Yes

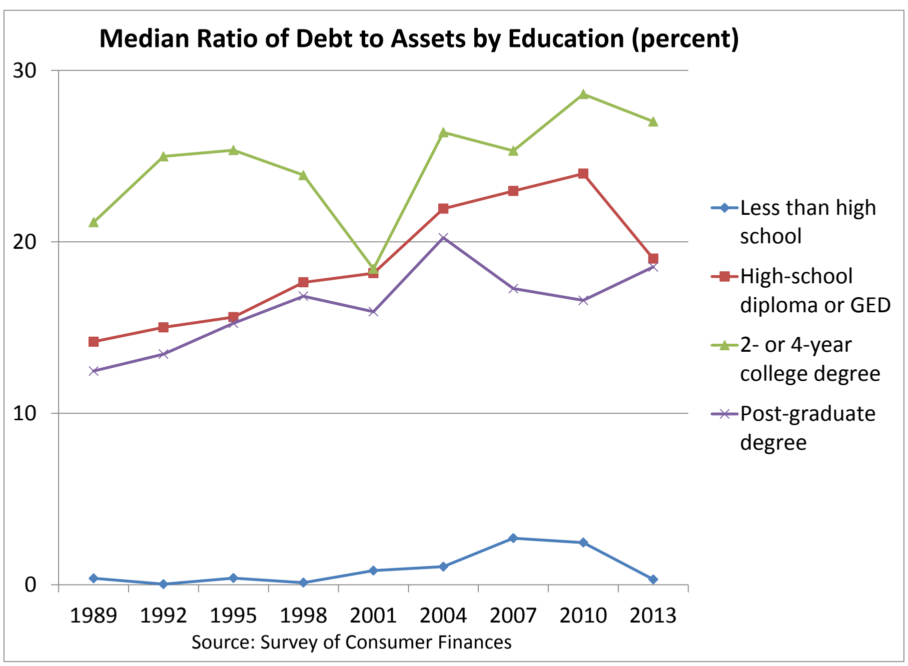
NOTE: p-value statistics are in parentheses; * denotes significance at ≤ 10%, ** denotes ≤ 5%, *** denotes ≤ 1%. An asterisk indicates the block of variables was included in the logit regression. See Table 1 for variable details. Data are from the Survey of Consumer Finances, comprising nine triennial waves between 1995 and 2013. Total observations are 34,479, on average, over the five implicates used in each regression. Standard errors are bootstrapped with 999 replications and are adjusted for imputation uncertainty. Sample weights are used in regressions.

Figure 1



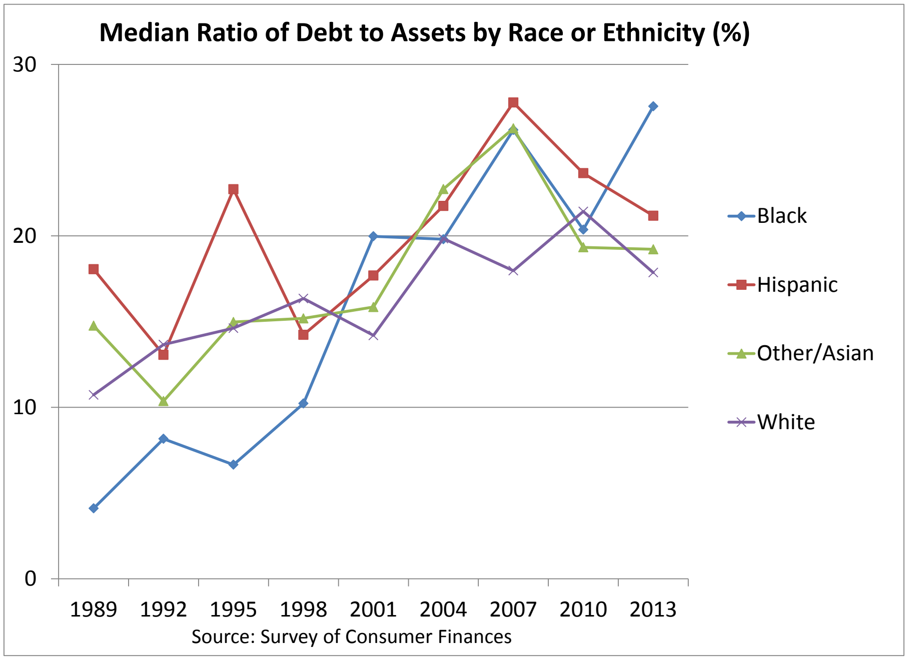
NOTE: Total debt is divided by total assets for each family. The median ratio among each group is shown.

Figure 2



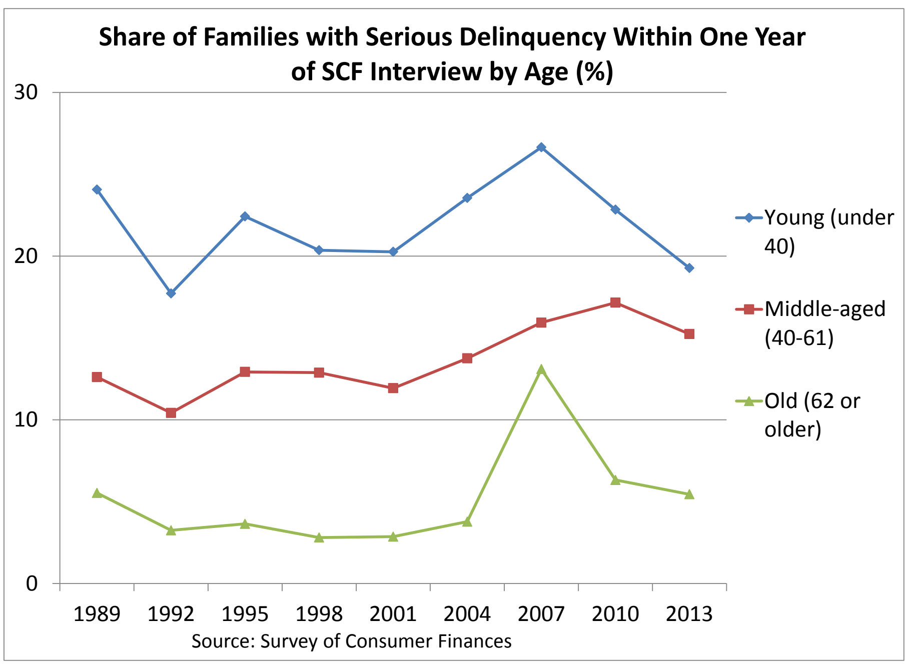
NOTE: Total debt is divided by total assets for each family. The median ratio among each group is shown.

Figure 3



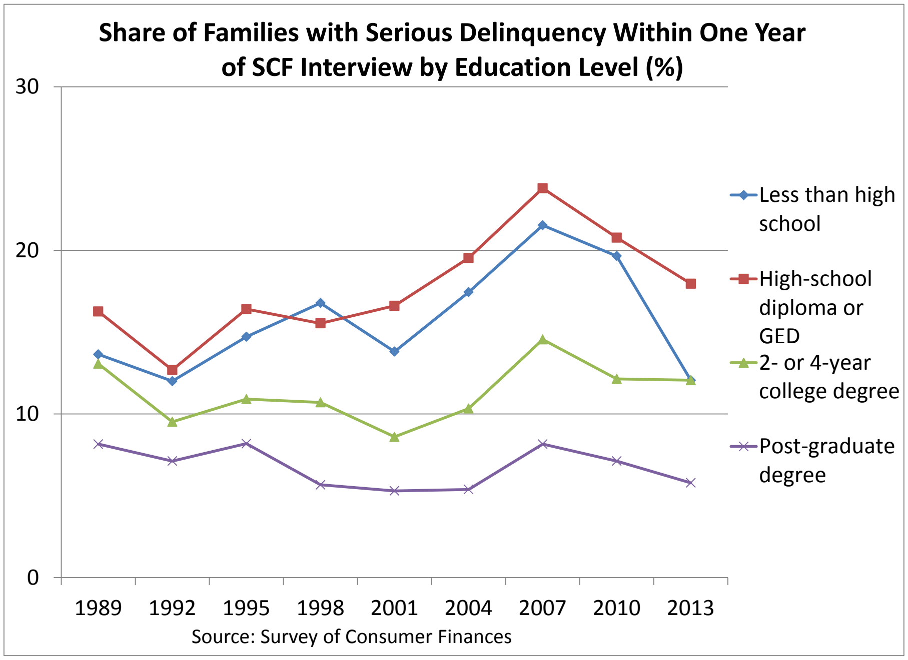
NOTE: Total debt is divided by total assets for each family. The median ratio among each group is shown.

Figure 4



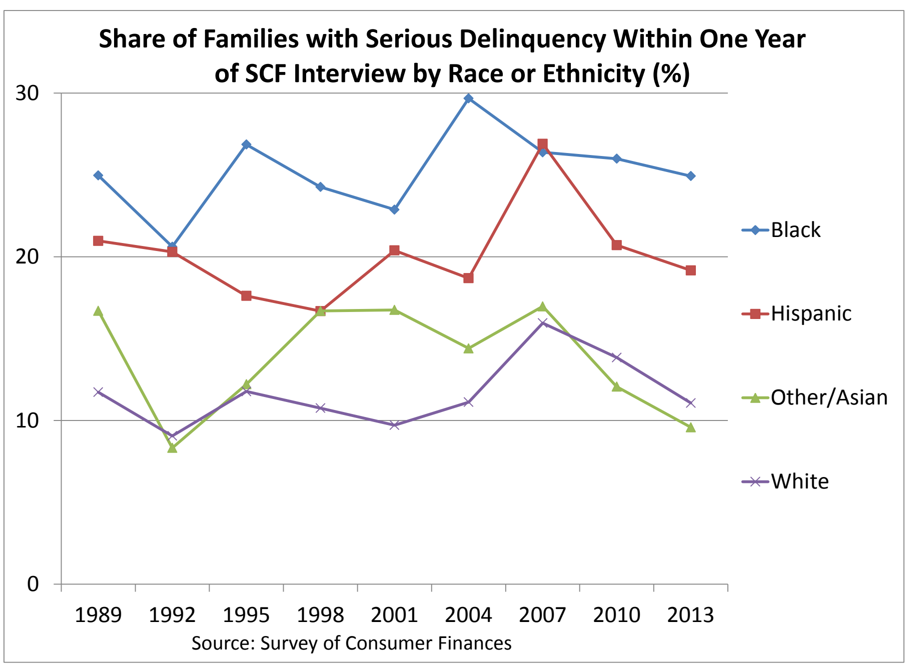
NOTE: Unconditional delinquency rates are shown—number of families with a serious delinquency in a group divided by the total number of families in a group.

Figure 5



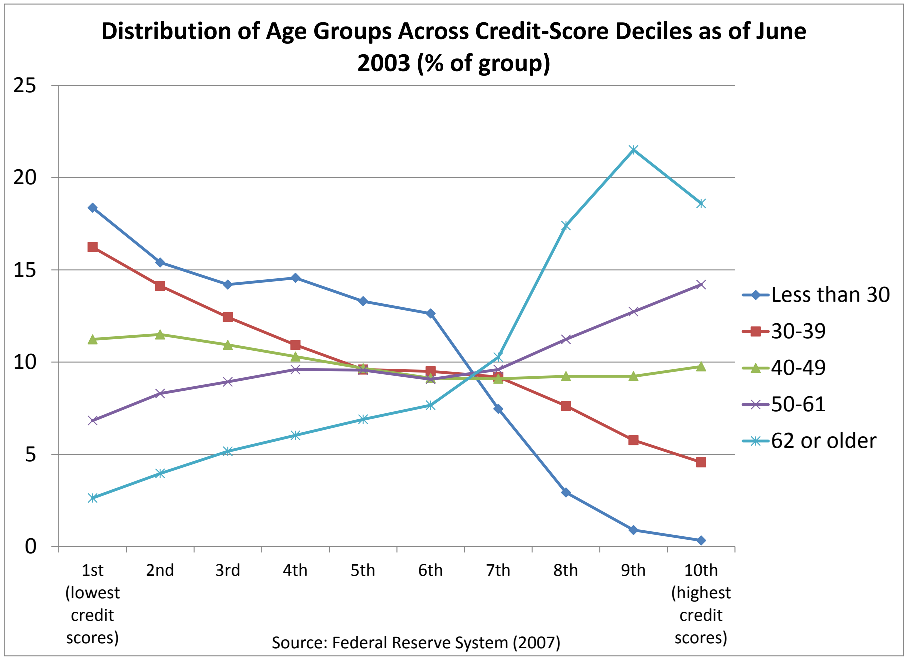
NOTE: Unconditional delinquency rates are shown—number of families with a serious delinquency in a group divided by the total number of families in a group.

Figure 6



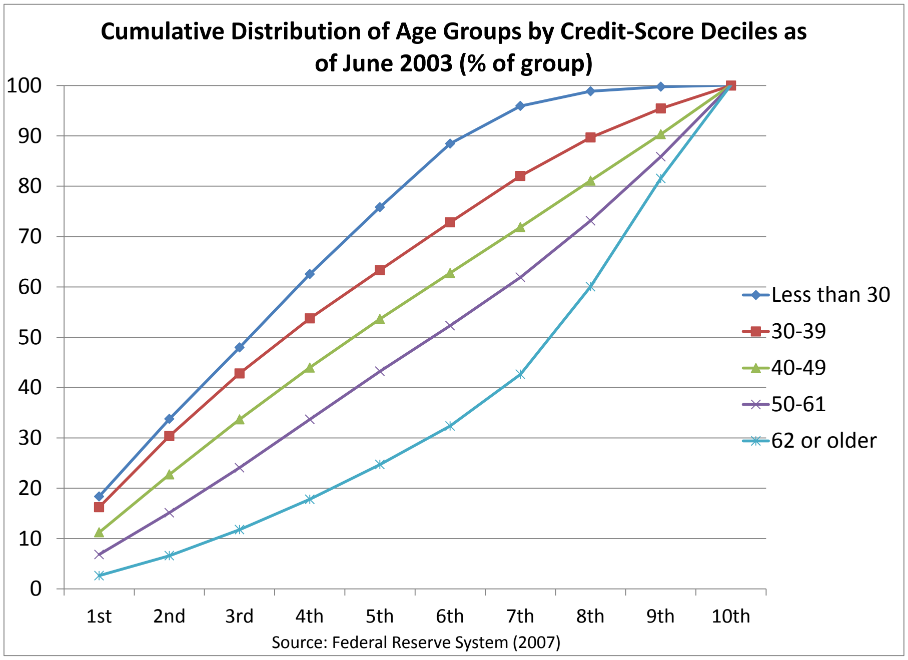
NOTE: Unconditional delinquency rates are shown—number of families with a serious delinquency in a group divided by the total number of families in a group.

Figure 7



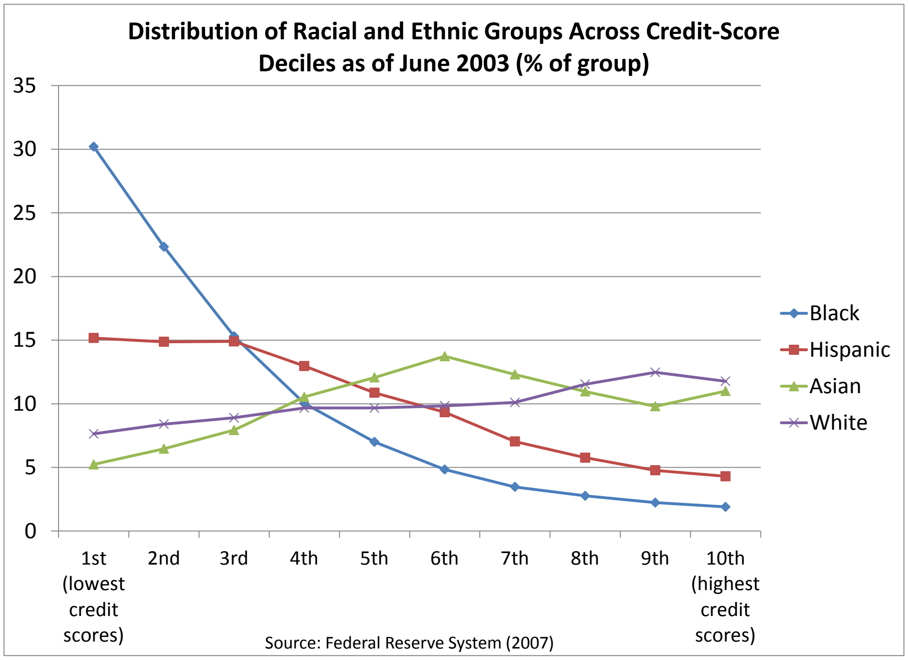
NOTE: Each data point represents the share of an age group assigned a credit score in the indicated decile of the overall distribution of credit scores. For example, 18.4 percent of individuals under 30 have a credit score that ranks in the lowest 10 percent of all credit scores while 2.6 percent of individuals 62 or older have a credit score in the lowest decile. Scores are based on the average of three credit scores: TransRisk Score, VantageScore and Federal Reserve Board Base Score.

Figure 8



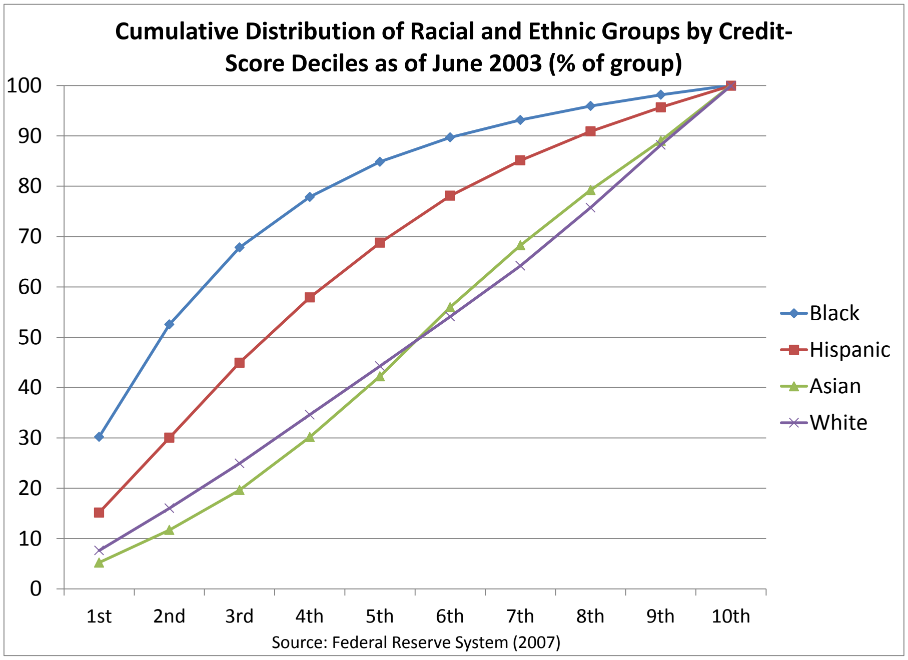
NOTE: Each data point represents the share of an age group assigned a credit score in the indicated decile of the overall distribution of credit scores or lower. For example, 75.8 percent of individuals under 30 have a credit score that ranks in the fifth decile or lower among all credit scores while 24.7 percent of individuals 62 or older have a credit score that ranks in the fifth decile or lower. Scores are based on the average of three credit scores: TransRisk Score, VantageScore and Federal Reserve Board Base Score.

Figure 9



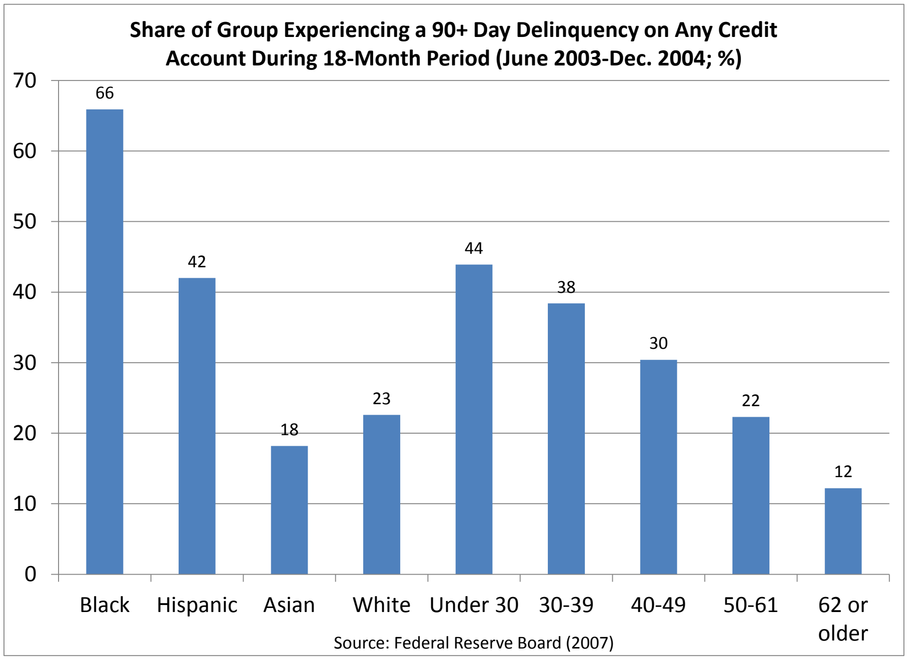
NOTE: Each data point represents the share of a racial or ethnic group assigned a credit score in the indicated decile of the overall distribution of credit scores. For example, 30.2 percent of blacks under 30 have a credit score that ranks in the lowest 10 percent of all credit scores while 5.2 percent of Asians have a credit score in the lowest decile. Scores are based on the average of three credit scores: TransRisk Score, VantageScore and Federal Reserve Board Base Score.

Figure 10



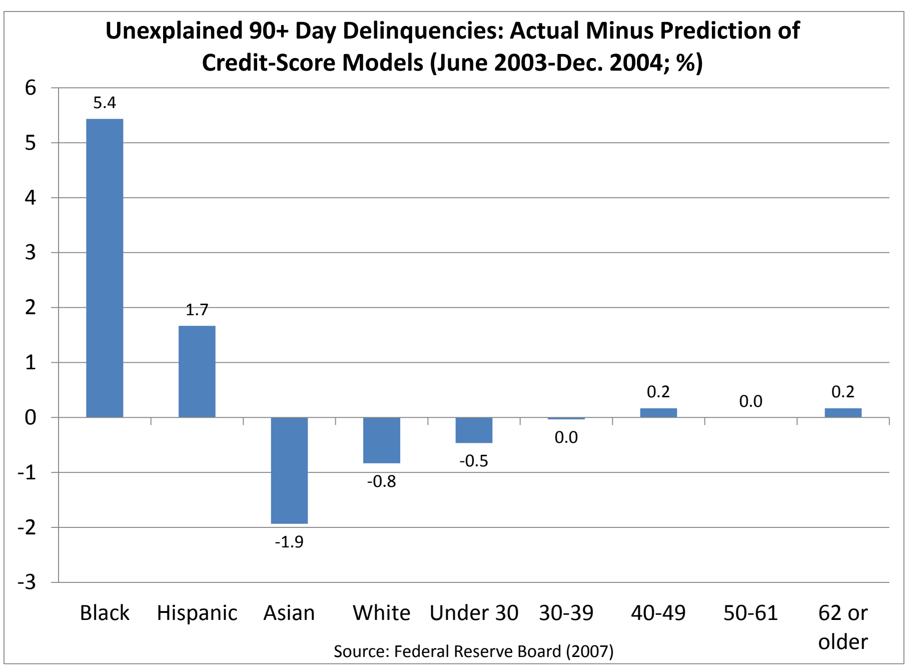
NOTE: Each data point represents the share of an age group assigned a credit score in the indicated decile of the overall distribution of credit scores or lower. For example, 84.9 percent of blacks have a credit score that ranks in the fifth decile or lower among all credit scores while 42.2 percent of Asians have a credit score that ranks in the fifth decile or lower. Scores are based on the average of three credit scores: TransRisk Score, VantageScore and Federal Reserve Board Base Score.

Figure 11



NOTE: See Table 17 of Federal Reserve Board (2007). Conditional delinquency rates are shown—number of individuals with a serious delinquency in a group divided by the total number of individuals in a group with a credit record.

Figure 12



NOTE: See Tables 18A-C. Based on the average of three credit scores: TransRisk Score, VantageScore and Federal Reserve Board Base Score.