CREDIT ACCESS IN THE UNITED STATES*

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Abstract

We construct new population-level linked administrative data to study households' access to credit in the United States. By age 25, Black adults, those who grew up in low-income families, and those raised in the Southeast or Appalachia already have significantly lower credit scores than other groups, and these differences persist throughout adulthood. These gaps translate into smaller credit balances, more credit inquiries, higher credit utilization, and greater reliance on high-cost alternative financial services. Evaluating two definitions of algorithmic bias yields opposing results. Scores are miscalibrated against traditionally advantaged groups: conditional on a score, Black and low-parental-income individuals fall delinquent more often. Yet scores are unbalanced against traditionally disadvantaged groups: among borrowers with no future delinquency, Black and low-parental-income individuals receive lower scores. Eliminating both biases and reducing gaps in credit access requires reducing systematic differences in delinquencies, which emerge in one's twenties through missed payments on credit cards, student loans, and other bills. Comprehensive measures of individuals' income profiles and observed wealth explain only a small portion of these repayment gaps. In contrast, most geographic variation in repayment reflects the causal effect of childhood exposure to place. Counties that promote upward mobility also promote repayment and expand credit access, suggesting that common place-level factors may drive behaviors in both credit and labor markets. We discuss suggestive evidence for several mechanisms of our results, including the role of social and cultural capital. We conclude that gaps in credit access by race, class, and hometown have roots in childhood environments. *JEL Codes:* G5, H0.

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I Introduction

Many aspects of our background, such as parental income, race, and our hometown, influence our outcomes in adulthood. Theoretically, access to affordable credit provides a pathway to overcome deficits in one's initial circumstances and achieve economic opportunity. To that aim, a large body of empirical work documents the effects of credit access on wealth accumulation and consumption smoothing. Credit scores also play an increasing role in screening applicants in other settings, such as insurance, housing, and labor markets. Understanding the extent to which the credit market provides a pathway to economic opportunity requires understanding how and why access to formal credit varies with one's inherited circumstances, such as race, class, and hometown. However, efforts to study these gaps have often been hindered by a lack of data sources linking credit records to demographic and income information. Such data limitations have prevented researchers from precisely quantifying differences in credit access by race, class, and place, much less investigating their determinants.

In this paper, we construct a new anonymized longitudinal dataset that combines credit bureau records with information from Decennial Censuses, Census surveys, and federal income tax returns for over 25 million individuals. Using these data, we provide new evidence on gaps in credit access in the United States, with particular attention to how credit access varies by race, class, and hometown.[1] We then investigate potential drivers of these differences.

We begin by measuring differences in rates of having a credit file and credit scores by race.[2] The vast majority of American adults have a credit file, indicating that they have some form of formal credit. However, the credit scores on these files vary considerably. In 2020, the average VantageScore 4.0 credit score was 719 for White, 621 for Black, 641 for American Indian and Alaska Native (AIAN), 670 for Hispanic, and 746 for Asian individuals. These gaps emerge before age 30 and remain largely stable throughout the life cycle. For example, the White-Black gap in mean credit scores is 97 points at age 30 and 92 points at age 60. Credit score gaps are larger when measured in medians than in means. The median credit score is 743 for White, 604 for Black, 625 for AIAN, 671 for Hispanic, and 779 for Asian individuals.[3] In other words, most White individuals are classified as "prime" borrowers, while a majority of Black individuals fall below the threshold required to qualify for a conventional mortgage.

While previous research has examined racial gaps in credit, less attention has been paid to the role of class or hometown. Following Chetty et al. (2020), we link individuals to their parents using dependent

[1] We measure race/ethnicity but refer to it as "race" throughout for brevity. For most analyses, we define class based on parental income, though we also consider parental education levels. We define hometown as the county where the child's parents lived when the child was between ages 0 and 23. In cases where a family moved during childhood, we assign children to counties in proportion to the number of years spent in that county.

[2] Existing studies documenting racial gaps in credit scores tend to rely on location-based proxy measures for race (Garon, 2022; Martinchek, 2024; Brevoort, Grimm and Kambara, 2015) or restrict attention to self-selected subsamples, such as mortgage applicants (Bhutta, Hizmo and Ringo, 2024; Consumer Financial Protection Bureau Office of Research, 2021; Gerardi, Lambie-Hanson and Willen, 2021; Bhutta and Hizmo, 2021). Some studies measure race gaps in credit reports using linked surveys (Stavins, 2020; Warren et al., 2024). Finally, Federal Reserve Board of Governors (2007) use linked SSA data to measure credit scores by race, following a mandate in Section 215 of the Fair and Accurate Credit Transactions Act of 2003 (FACT Act).

[3] These gaps in credit scores by race are larger than those found in previous studies using ZIP-code-based proxies for race and are substantially larger than those found using data from mortgage applications or originations. We replicate both attenuation patterns in our data by aggregating geographies and restricting the sample to those who have a mortgage. See Appendix Table A.1.

claiming on tax returns. The share of individuals with a credit file increases modestly with parental income, rising from 90% to 94% when comparing individuals from the bottom versus the top quintile of the parental income distribution. We find variation in credit scores by parental income that are of similar magnitudes to the differences by race. Average credit scores for individuals between the ages of 35 and 42 with a credit score range from 630 for those with parents in the bottom quintile to 740 for those with parents in the top quintile. Similarly, children whose parents did not complete high school have an average credit score of 638, in contrast to 725 for those with a parent who completed a bachelor's degree.[4] Despite these class differences in credit scores, parental income and education only partially explain racial score gaps. For example, Black individuals from the 90th percentile of parental income have similar average credit scores as White individuals from the 25th percentile. We also find large gaps in credit scores based on where children grew up. Among the 100 largest counties, people who grew up in Bergen County, New Jersey have the highest credit scores on average (724), while those who grew up in Baltimore, Maryland have the lowest (627), with the roughly 100 point disparity on the same order of magnitude of the race and class gaps above. Differences in credit scores across hometowns persist within race and parental income. Among White individuals from the 25th percentile of parental income, those who grew up in Kings County, New York (Brooklyn) have the highest credit scores (719), while those from Marion County, Indiana (Indianapolis) have the lowest average credit scores (629).

These differences in credit scores appear to translate into credit constraints faced by lower-scoring groups. Black individuals and those born to parents in the bottom quintile of the parental income distribution hold roughly a third of the average balances of those in the top regions of the income distribution. The one category of loans for which we do not see this pattern is student loans, which are uniformly supplied to college enrollees regardless of credit score or other measures of creditworthiness. Black individuals between the ages of 35 and 42 in 2020 had nearly twice as much student debt as White individuals (an average of $18,880 versus $10,020, inclusive of zeros for those without loans), despite lower rates of college attendance. Groups with lower credit scores also have higher rates of credit inquiries and higher credit card utilization rates, indicating they are searching for more credit and using more of the credit they have. They also have greater use of alternative financial services such as payday loans. Across geographies, people from areas with lower credit scores report in surveys that they have more difficulty obtaining money to cover an unexpected need. Finally, the time path of debt accumulation over the life cycle aligns with a credit constraint interpretation: credit score gaps expand during the mid-twenties at the same time that balances and the number of accounts diverge. In short, we find large differences in credit scores by race, class, and hometown that are consistent with differences in the supply of formal credit to these groups.

The second part of the paper analyzes the determinants of these gaps. We begin by studying the role of algorithmic bias in credit scores. A natural reason lenders might restrict access to credit is that they fear they will not be repaid. Credit scores aim to predict future debt repayment using only the information in one's credit file, which includes repayment history, balances, credit utilization, and the age of one's accounts. While scoring algorithms cannot use information on race, income, location, or age to generate scores, there

[4] Credit score gaps by parental education persist after controlling for parental income. Among individuals with parents from the 25th percentile of the income distribution, those with a parent who completed a bachelor's degree have a credit score that is 53 points higher on average than those whose parents did not complete high school.

is growing recognition that seemingly neutral prediction algorithms could generate unwarranted disparities (Fourcade and Healy, 2013; Passi and Barocas, 2019; Barocas and Selbst, 2016; Kleinberg et al., 2018; Kiviat, 2019; Burrell and Fourcade, 2021; Black et al., 2022; Elzayn et al., 2025). The existing literature has focused on two distinct definitions of algorithmic bias (Kleinberg, Mullainathan and Raghavan, 2016). The first is *calibration*: conditional on a given credit score, do individuals of different groups have the same rate of subsequent delinquency? The second is *balance*: among those with the same future repayment outcomes, did members of different groups receive similar credit scores?[5] We measure each type of bias of the credit scoring system in the U.S.

From a *calibration* perspective, we find that credit scores underestimate race and class differences in future delinquencies, implying that they have a calibration bias against groups with higher credit scores on average.[6] Among individuals aged 35-42 with a credit score of 650,[7] 61% of Black individuals fall delinquent in the subsequent four years, compared to just 47% of White individuals and 39% of Asian individuals.[8] We find similar patterns by class: conditional on a 650 credit score, 54% of borrowers from the bottom quintile of the parental income distribution fall delinquent in the following four years, compared to 43% for those from the top quintile.[9] This calibration bias is largest for those in their twenties, reflecting the difficulty of predicting delinquencies at younger ages, perhaps due to less information in the credit file. In sum, these patterns suggest that the large gaps in credit scores that we measure by race, class, and hometown would be even larger if credit scores could more accurately predict group-level differences in future delinquencies.[10]

From a *balance* perspective, however, we find that credit scores are biased against members of groups with lower average credit scores. Among individuals with no delinquencies in the subsequent 4 years, Black individuals' credit scores are on average 71 points lower than the credit scores of White individuals, and those with parents in the bottom quintile of the income distribution receive credit scores that are roughly 76 points lower than those from the top quintile. These gaps persist but with smaller magnitudes even if we restrict to individuals with "spotless" credit records before and after the score is measured. Among

[5]The balance condition is sometimes referred to as "equal-odds" in the computer science literature (Berk et al., 2017; Zafar et al., 2017). For a binary classification, this condition is satisfied when false negative and false positive rates are equal across groups.

[6]We define delinquency as being 90 or more days past due on any line of credit. This delinquency definition aligns with the target estimand of the credit score (VantageScore Solutions, 2022).

[7]We condition on a 650 credit score as this falls roughly in between the average credit score for Black and White individuals. The calibration biases we identify are smaller at lower credit score values and larger for higher credit score values.

[8]These findings echo those of Bhutta and Canner (2013) and Bayer, Ferreira and Ross (2016), who use linked Home Mortgage Disclosure Act (HMDA) data to show that Black borrowers have higher mortgage delinquency rates than White borrowers with similar credit scores, as well as Dobbie et al. (2021) who find evidence of lending bias against immigrant and older populations in the United Kingdom. By contrast, Blattner and Nelson (2021) argue that credit scores do not exhibit calibration bias for marginal home loans—a finding that suggests perhaps mortgage issuance relies on additional information beyond the credit score that mitigates the population-level bias we document.

[9]These results are robust to alternative scoring methods derived from predicted delinquencies, suggesting they are driven by the information in the credit file rather than the VantageScore 4.0 scoring algorithm.

[10]Our findings dovetail with recent work on credit-file content. Blattner and Nelson (2021) show that thin files lump minority borrowers with solid repayment histories together with riskier peers; our results suggest that those thin files may be due to early-adulthood credit constraints arising from non-repayment. Using linked mortgage data, Fuster et al. (2022) find that adding more account information would widen Black–White score gaps, reinforcing our evidence that scores understate racial differences in delinquency. Reforms that drop derogatory marks or expand reporting raise overall credit access but leave sizable racial gaps in risk and borrowing terms (Dobbie, Keys and Mahoney, 2017; Liberman et al., 2018).

those with no late payments between 1997 and 2020, the average 2012 credit score for Black individuals is roughly 13 points lower than it is for White individuals, and the average 2012 credit score for those from the bottom quintile of parental income is roughly 12 points lower than it is for those from the top quintile. These lower credit scores suggest that Black individuals and those from low-parental-income backgrounds face greater credit constraints even when restricting to those who perfectly repay their debts.[11]

Our results show how different definitions of algorithmic bias illuminate different patterns and experiences in the credit market. Black and Hispanic individuals are more likely to fall delinquent than White individuals with the same credit score; but among the set of people who do repay their debts ex-post, Black and Hispanic individuals have received ex-ante lower credit scores than White individuals. More generally, when groups differ in their base rates of debt repayment, no algorithm can be simultaneously unbiased according to both calibration and balance definitions, except in the trivial case where it predicts repayment perfectly (Kleinberg, Mullainathan and Raghavan, 2016). Thus, the only remedy for removing algorithmic bias in both dimensions and to reduce the observed differences in credit scores across groups is to eliminate the underlying group-level differences in non-repayment. We turn our attention in the remainder of the paper to understanding the drivers of non-repayment.

We first note that these group-level differences emerge early in the life cycle. By age 25, over 69% of Black individuals have a 90+ day late payment on their credit report, in contrast to 31% for White individuals. Similarly, 60% of individuals from the bottom quintile of the parental income distribution have a 90-day late payment at age 25, in contrast to 15% for those from the top quintile of the parental income distribution. Most of these delinquencies arise from falling behind on credit cards, student loans, and other types of bills that have been sent to collections (e.g., phone or utility bills, medical bills, etc.), while mortgages and auto loan delinquencies are a very small share. As we discuss further in Section V, these patterns suggest that differences in credit terms are likely not driving the group-level differences in delinquency rates early in life.

Differences in income provide a potential explanation. Using linked tax return information, we find that those with higher incomes are less likely to fall delinquent. However, including controls for more than a decade's worth of past and future income explains only 30% of the overall racial gap in repayment, just 20% of the racial gap conditional on the credit score, and about 40% of the class gap (conditional or unconditional on the credit score). Race- and class-based differences persist even among workers with stable wage growth and continuous employment at the same firm. Including further controls for measures of wealth, such as cumulative 401k contributions, home equity values, and more comprehensive measures of liquid and total wealth from the Survey of Income and Program Participation (SIPP) leaves the race gaps unchanged and still does not eliminate the class gaps. Similarly, differences in incomes do not explain variation in repayment across hometowns. Places with high repayment are also places with high repayment conditional on the same level of adult income (correlation of 0.95). The fact that income and wealth do not eliminate gaps in repayment is consistent with the fact that differences in intergenerational income mobility widen in people's thirties and forties, whereas the repayment gaps arise in their early twenties. It is also

[11] Note that since the credit score can only take into account information in one's credit file, Black and lower parental income individuals with perfect repayment histories must systematically differ on other dimensions such as balances, credit utilization, and the age of one's accounts.

consistent with experimental evidence from Bartik et al. (2024) who find that cash transfers of $1,000 per month for 3 years do not significantly affect delinquency rates.[12]

The early life divergence in repayment behavior suggests a role of childhood environment. As further evidence of this, we find that parental credit scores strongly predict children's repayment even controlling for income and wealth of both the child and the parents: moving from the lowest to highest parental credit score corresponds to roughly a 44 percentage point difference in future delinquency. This suggests that the way families manage their finances plays a strong role in explaining children's own financial behaviors in their twenties and beyond.

To further isolate a causal role of childhood environments, we study the role of one's hometown. We follow Chetty and Hendren (2018*a*) and exploit variation in the timing of parents' cross-county moves. We find that most of the geographic variation in repayment between hometowns is driven by the causal effect of childhood exposure to those places. Children who spend more time growing up in a place where other people repay debts are themselves more likely to repay, even conditional on their income in adulthood. Moreover, we find that the convergence of one's repayment behavior to the repayment behavior of others in the same hometown is race-specific, suggesting that race gaps would be largely eliminated if Black and White children grew up in counties with no racial gap in repayment.

Why might hometowns cause differences in repayment behavior? As a first clue, we show that counties that promote debt repayment also promote higher incomes for children who grow up in them, as measured in Chetty and Hendren (2018*b*). Yet debt repayment is not simply driven by higher incomes, as these counties also promote debt repayment conditional on income in adulthood. This suggests common underlying factors across place promote higher incomes and debt repayment.

What might these factors be? In the last section of the paper, we use previous research in sociology and economics to guide an exploration of potential mechanisms, place our results in the context of this work, and propose areas for future work. We focus our exploration on the roles of financial literacy, differential exposure to economic shocks, and social capital. We find the most support for the role of social networks in driving the repayment gaps we observe. Families and social networks can provide direct financial support and an ability to obtain money when one needs it, and we find some evidence for this potential channel. However, mirroring strong correlations found with upward income mobility in Chetty et al. (2022), we find stronger evidence that places that exhibit more cross-class economic connections likely provide childhood experiences and role models that shape one's understanding of how formal credit works and influence how one manages their finances in adulthood—a finding that aligns with existing evidence of how one's earlier-life experiences shape their financial lives (Malmendier and Nagel, 2011, 2016; Malmendier and Wachter, 2021). These two pathways, financial networks and learned financial decision-making strategies, can reinforce each other in the face of adverse events. Individuals embedded in distressed networks who experience economic shocks are more likely to fall back on perhaps more familiar but costly products—payday loans, auto title loans, pawn shops—thereby deepening delinquency. Indeed, once we use survey data to condition on use of alternative financial services, the race, class, and hometown gaps in repayment all but disappear.

[12] They do find an increase in transfers to family members and vehicle consumption (that appears to be combined with increased auto loans).

In summary, our results show that credit constraints in adulthood are driven by delinquencies that occur early in one's life and have roots in one's childhood environments.

Our paper relates to several strands of previous literature.[13] First, there is a large literature seeking to understand the determinants of credit market behaviors. Lusardi and Mitchell (2014, 2023) document racial and socioeconomic differences in measures of financial literacy. We replicate these differences but do not find evidence that they explain racial gaps in repayment. Malmendier and Nagel (2011, 2016); Malmendier and Wachter (2021) find that past experiences can shape behavior in credit markets.[14] Particularly relevant to our findings, Arthi, Richardson and Van Orden (2024) document long-run behavioral effects of traumatic financial experiences among Black individuals through the lens of the failure of the Freedman's Savings Bank. Most closely related to our work on variation across hometowns, Keys, Mahoney and Yang (2023) study adults who move across locations and find minimal effects of adult location on late payments; our results suggest that repayment outcomes are instead shaped through one's childhood environments. Importantly, our finding of effects of childhood exposure to places on credit scores and repayment is consistent with Miller and Soo (2021) who study the Moving to Opportunity (MTO) experiment and find effects of MTO on children's future credit scores but no impacts on adult credit scores. Our results are also consistent with Brown, Cookson and Heimer (2019) who find that childhood exposure to financial institutions on Native American reservations leads to higher credit scores and fewer delinquencies.

Another strand of literature measures the relationship between credit and intergenerational mobility. Using panel data on credit reports, Hartley, Mazumder and Rajan (2019) document strong intergenerational persistence in credit scores. Braxton et al. (2024) use credit data linked to the LEHD to study the causal effect of parental credit access on incomes of children in adulthood, which complements our focus on access to the credit market for the children's generation. While much of this literature finds beneficial impacts of credit access (e.g.,Black et al. (2020) find that increasing credit access to students through higher loan limits raises educational attainment and subsequent earnings), our results reveal that credit market access itself remains deeply stratified by parental income, race, and hometown, mirroring and potentially reinforcing the very gaps it could in principle mitigate. In this sense, our results relate to Bayer, Charles and Park (2025) who highlight the role of capital held by one's racial group in shaping intergenerational mobility. Their finding that controlling for race-specific measures of capital narrows upward mobility gaps aligns with our findings of the importance of one's environment and network in shaping repayment and access to credit.

Our paper also relates to work documenting greater financial strains faced by Black households driven by lower income and wealth within one's family and social network (Stack, 1974; McAdoo, 1978; Taylor et al., 1996; Chatters et al., 2008; St. Vil, McDonald and Cross-Barnet, 2018; Massey and Denton, 2019;

[13] In a related literature, sociologists have written extensively about the promise and peril of expanding credit access in the United States, especially its implications for race and class inequality (Hyman, 2011; Prasad, 2012; Krippner, 2012, 2017; Dwyer, McCloud and Hodson, 2011; Thurston, 2018; Quinn, 2019; Wherry, Seefeldt and Alvarez, 2019; Carruthers and Ariovich, 2010).

[14] Several other papers further underscore that credit gaps arise from a complex interplay of financial structures, household resources, and behavioral responses. Fulford and Low (2024) highlight the importance of expense shocks as a driver of consumer loan delinquency and financial distress. Scott-Clayton and Li (2016) show that Black college graduates have larger student debt burdens than White graduates immediately after graduation, and this gap triples over the next few years due to differential repayment. Ganong and Noel (2019) document present-biased behavior among households facing UI benefit exhaustion. Finally, Brown et al. (2016) find that some financial literacy interventions modestly improve credit market outcomes such as delinquency and collections.

Derenoncourt et al., 2024). Previous literature documents that Black young adults are more likely to provide financial support to parents and siblings, with implications for longer-run racial wealth inequality (Chiteji and Hamilton, 2002; McKernan et al., 2014; Lanuza, 2020). Our results highlight how intergenerational persistence in credit market behaviors and social capital may play a role in the persistence of wealth gaps across generations.

Our findings also relate to a literature that documents racial gaps in lending markets, especially in auto and mortgage markets that involve loan officers (Munnell et al., 1996; Rugh and Massey, 2010; Rugh, Albright and Massey, 2015; Bayer, Ferreira and Ross, 2016; Taylor, 2019; Lanning, 2021; Bhutta and Hizmo, 2021).[15] In algorithmic credit card lending, however, Butler, Mayer and Weston (2023) do not find racial gaps, even among the same borrowers for whom they find racial disparities in auto loan interest rates and approval rates, suggesting that racial disparities are more prevalent when there is more scope for human decision-making (e.g., from a loan officer).[16] Relative to this literature, our contribution is to measure algorithmic bias in the determination of credit scores. This algorithmic bias is distinct from the potential bias of creditors making lending decisions if they combine credit scores with additional information that includes or correlates with one's race or background. Our results also show that the gaps in repayment have emerged by the time individuals are in their mid-twenties, primarily on credit cards, student loans, and other bills that are not subject to loan officer decisions, highlighting an important focus on the determinants of credit market behaviors among youth and young adults.

The remainder of the paper is organized as follows. Section II provides more details on the data sources, the linkage, and the construction of the sample. Section III documents credit score gaps by race, class, and hometown and the evidence of the resulting credit constraints faced by those individuals. Section IV investigates how credit scores relate to delinquency and quantifies algorithmic biases in credit scores. Section V studies the types of credit on which people fall delinquent and the age profile of those delinquencies. Section VI evaluates whether income or wealth can explain these differences in delinquencies. Section VII investigates the role of childhood environment in shaping credit market behavior. Section VIII discusses the potential mechanisms behind childhood exposure effects, and Section IX concludes. County-level data on average credit scores, delinquency, and credit balances by race, parental income, and hometown are publicly available on the Opportunity Atlas: www.opportunityatlas.org.

[15] Argyle et al. (2025) find that White bankruptcy trustees discriminate against minority filers more for Chapter 13 bankruptcies, where they have more discretion, than for Chapter 7 bankruptcies.

[16] A GAO report finds higher APR in majority Black ZIP codes: 2.17 points higher in majority Black neighborhoods than majority White neighborhoods. The gap falls to 0.72 points when controlling for credit score, presence of revolving debt, income, and state and month fixed effects (United States Government Accountability Office, 2023). See Table 7 on pages 86-87 of the GAO report. Raymond (2024) finds that the entry of algorithmic investors into housing markets reduces racial gaps in home sales prices. Similarly, Bartlett et al. (2022) identify 40% less discrimination among FinTech lenders compared to traditional lenders.

II Data

II.A Sample

We use an anonymized hashing procedure to link data from a major credit bureau with administrative and survey data housed at the U.S. Census Bureau. We focus our analysis on two primary samples of the U.S. population: a population sample and an intergenerational sample.

Population Sample Our population sample is a random 1% sample of individuals with Social Security numbers (SSN) who appear in the Decennial Census in 2000 or 2010.[17] We link these individuals to three Census and administrative data sets: (1) the 2000 and 2010 Census short forms, which aim to cover the entire population; (2) the 2000 Census long form and 2005-2019 American Community Survey (ACS), which cover approximately one sixth of households and 2.5% of households annually, respectively; and (3) federal income tax returns spanning 1969-2021, with complete coverage for 1994-1995 and 1998-2021 (U.S. Department of Commerce, Bureau of the Census, 2000, 2003, 2014).[18] We also link these data to the Survey of Income and Program Participation, which provides survey measures of wealth for around 50,000 households in each panel. We then use the procedure described in Appendix A to merge this sample to an individual panel of credit bureau records in four-year intervals from June 2004-2020. Importantly, the major credit bureau and the Census Bureau agreed on the subset of SSNs corresponding to the sampling universe, which means that, by construction, unmatched individuals in this sample do not have a credit file with this major credit bureau.

Intergenerational Sample Our intergenerational sample mirrors the primary analysis sample in Chetty et al. (2020), which was constructed from Census data linked to tax return information in order to study intergenerational income mobility. We start with all individuals with Social Security numbers who were born between 1978 and 1985. We again link credit records in four-year intervals from June 2004-2020 to the Census and administrative data sets (1)-(3) discussed above. Following Chetty et al. (2020), we then link each individual to their parents using the first parent to claim them as a dependent on a tax return in our data.[19] In addition to credit files of those born between 1978-85, we also obtain a subsample of credit files of their parents by linking them to a 10% random sample of credit files for individuals born between 1935 and 1970—a cohort range that includes the vast majority of the parents in our sample.

Both our intergenerational and population samples are restricted to the subset of people who can be matched to a Protected Identification Key (PIK) in the Decennial Censuses or ACS. About 90-93% of De-

[17] This restriction drops SSN holders who do not reside in the U.S. and those whose name and address information on the Census short forms are not linkable to Census records. Census publications note that over 90% of people in the Decennial Census receive a Protected Identification Key (PIK) (Mulrow et al., 2011*b*). PIKs are assigned by the Census Bureau using information such as SSNs, dates of birth, names, and addresses. See Wagner and Layne (2014) for a detailed description of the PIK assignment process.

[18] Note that W-2s are only available starting in 2005.

[19] We limit our analysis to children born during or after 1978 because many children begin to leave the household at age seventeen (Chetty et al., 2014), and the first year in which we have dependent claiming information is 1994. We include the universe of birth cohorts up through 1985 to ensure all individuals have reached adulthood by 2004, the first year for which we have credit bureau data.

cennial Census records in 2000 and 2010 are able to be assigned a PIK, which is required for linkage to other datasets like credit records and tax returns (Mulrow et al., 2011*a*; Wagner and Layne, 2014). Moreover, the 2010 Census Coverage Measurement Survey estimates that 5.3% of people in U.S. households are omitted in the 2010 Decennial Census, consistent with similar findings in the 2020 Post-Enumeration Survey (Khubba, Heim and Hong, 2022). Thus, there can be people missing from Decennial records or in the Decennial but without a PIK. Nonetheless, our samples of people who obtain a PIK are more comprehensive than those used in existing studies of racial bias that have linked Census records to other datasets, such as mortgage applicants from the Home Mortgage Disclosure Act (HMDA) files.

II.B Variable Definitions

Credit Bureau Variables The data from the major credit bureau include a full snapshot of summary attribute information in four-year intervals pulled in June 2004 through June 2020. Each snapshot contains comprehensive information about credit balances for each type of credit (credit cards, student loans, mortgages, auto loans, etc.). It also contains repayment information, including incidences of late payments of different durations (30 days, 60 days, 90 days, etc.), broken out by type of credit. We also observe information on credit inquiries, credit limits, bankruptcy filings, ages of accounts, and other credit events.

In addition to information from the credit file, the credit bureau data include a VantageScore 4.0 credit score, which uses credit file information to measure individuals' creditworthiness on a scale of 300 to 850. VantageScore 4.0 is one of several scoring methods intended to predict an individual's likelihood of falling 90 or more days delinquent on any line of credit within the next two years (Gibbs et al., 2024). Henceforth, we refer to the VantageScore 4.0 as the "credit score" since it is the only version of a credit score we use.[20] While the details of how these scores are constructed are not publicly disclosed, credit bureaus are prohibited from using information outside of the credit report, such as race, income, address, or even age, to determine one's score. To assess the robustness of our results to different scoring methodologies, we replicate our credit score analysis using our own predictions of 90+ day delinquencies.[21] We find similar patterns across methods, suggesting that the properties of the credit score that we identify are a structural feature of the predictive content of the information in credit reports, not the exact scoring methodology.

Income, Education, and Race We measure race using the information that individual respondents or a household member report on the 2000 and 2010 Census short forms and the American Community Survey (ACS), following the methods in Chetty et al. (2020). We prioritize the 2010 Census short form, then the

[20] VantageScore 4.0 targets the same objective (odds of 90+ day delinquencies) as the more commonly used FICO score. A primary difference is that it tends to score more "thin" files. For example, FICO requires tradelines to have been open for at least 6 months and updated within the last 6 months, restrictions that are not used in VantageScore 4.0 (VantageScore Solutions, 2022; Parrent and Haman, 2017). This means that our estimates of the fraction of the U.S. population with a credit score would in principle be lower if we were to use FICO instead of VantageScore 4.0.

[21] Note that, as with industry scoring methods, we predict a borrower's likelihood of falling 90 or more days delinquent on any line of credit they currently hold. Our predictions are based on a logit regression of 90+ day delinquencies on the VantageScore 4.0, as well as credit card, student loan, auto loan, and mortgage loan balances, all in both logs and levels with dummies for non-positive balances to avoid dropping them when taking logs. Presumably, prospective lenders find one's predicted repayment on existing debts informative of their likelihood of repayment on the marginal debt. We return to a discussion of this below when considering measures of algorithmic bias.

2000 Census short form, and finally the ACS. We use these data to construct five main racial groups—non-Hispanic White, non-Hispanic Black, Hispanic, non-Hispanic Asian, and non-Hispanic American Indian and Alaska Native (AIAN).[22] We note that there is of course heterogeneity in outcomes across all subgroups within these five groups, so that our conclusions may not apply uniformly to subgroups within each of these populations. For simplicity, we use "White" to refer to non-Hispanic White individuals, "Black" to refer to non-Hispanic Black individuals, "AIAN" to refer to non-Hispanic American Indian and Alaska Native individuals, and "Asian" to refer to Non-Hispanic Asian individuals.

In our intergenerational sample, we again follow Chetty et al. (2020) and measure parental income each year using the total pretax income of the primary tax filer and their spouse (if applicable), which we label family or household income. In years where a parent files a tax return, we define household income as the sum of Adjusted Gross Income, social security payments, and tax-exempt interest payments, as reported on their 1040 tax return. In years where a parent does not file a tax return, we define household income as W-2 income when available. Otherwise, we consider household income for non-filers to be zero. For our primary analysis, we define parental income in the child's youth as the mean household income over the five years in which the child is ages 13-17 (or the subset of those years for which we have tax data).

In addition to parental income, we also proxy for "class" using measures of parental education. We obtain the parental educational status of children whose parents were surveyed by the ACS at some point between 2005 and 2019. We define parental education using the maximum educational status between parents.

We also consider the role of an individual's adult income in shaping their repayment behavior. For those who file taxes, we define household income in the same manner as for parents (sum of Adjusted Gross Income, social security payments, and tax-exempt interest payments, as reported on their 1040 tax return). We also define individual income as wage income reported on their W-2, in addition to self-employment and other non-wage income reported on their 1040 tax returns. We assign individuals who are married and filing jointly half of the self-employment and other non-wage income. For non-filers, we define both individual and household income as total wage earnings from W-2s, or as 0 if no W-2 is filed.

Wealth In addition to income data, we also use several measures of wealth. First, we use data from a data analytics provider that focuses on the real estate market. We use data from their tax assessment files, which are drawn from all public county tax assessments in the U.S., to link to individuals in our sample. These data are then linked by property to valuation estimates, which are calculated based on recent transactions of similar properties. We use both home value and home equity in our analysis. Second, we construct a measure of retirement savings using information from tax forms. Following Choukhmane et al. (2024), we use deferred compensation from Box 12 of the IRS W-2 tax form, which includes savings for retirement, including 401k and 403b contributions. We cumulate these from 2005 to 2016.

In addition to these measures of wealth based on administrative data, we also use more comprehensive wealth data from the Census Bureau's Survey of Income and Program Participation (SIPP), which is a nationally representative, longitudinal survey. The SIPP includes questions about all major asset categories,

[22] Roughly 97.3% of children in our intergenerational sample fall into one of these five groups (Chetty et al., 2024).

including home equity, retirement accounts, stocks, bonds, vehicles, etc., as well as corresponding questions on debt. We combine these measures to create net wealth values for all linked respondents in our sample.

II.C Survey Measures of Expenditure, Alternative Financial Services, and Financial Literacy

To complement the administrative and credit bureau data, we rely on a variety of survey sources that provide detailed information on households' spending flows, liquidity constraints, and financial literacy. First, we draw on the Federal Reserve Board's triennial Survey of Consumer Finances (SCF)—–specifically the 2013, 2016, 2019, and 2022 waves (Board of Governors of the Federal Reserve System, 2023). The SCF is a nationally representative survey that provides detailed estimates of balance-sheet items, payment behavior, and use of alternative financial services. In the context of this paper, the SCF provides (i) measures of financial literacy, (ii) self-reported incidences of missed payments, (iii) indicators of payday loan usage that we exploit to benchmark the prevalence of "alternative" credit across the income and racial distribution, and (iv) measures of transfers between family and friends. Second, we fielded a bespoke online survey on the Prolific Academic platform to cover margins that are unobservable in either tax data or the SCF. The instrument was administered in May-June 2025 to 754 U.S. Prolific participants aged 22–30 who racially identify as Black or White.[23] Third, we use both the 2023 wave of the Panel Study of Income Dynamics (PSID) (Panel Study of Income Dynamics, 2025), and the 2015-2023 waves of the Consumer Expenditure Survey (CEX) (U.S. Department of Labor, Bureau of Labor Statistics, 2022) to measure differences in consumption by group and transfers within kin networks. Fourth, we use the National Financial Capability Study (NFCS) to measure geographic variation in financial literacy (Lin et al., 2022).

III Differences in Credit Access

We begin by measuring differences in credit access in the U.S. by race, class, and hometown. We use the credit score as a proxy for credit access. Later, we provide evidence supporting the interpretation that groups with lower credit scores face greater credit constraints.

III.A Credit "Invisibles"

We begin by documenting the share of individuals who have a credit file in the U.S. in 2020. By age 30, roughly 91% of the U.S. population that has an SSN also has a credit file with the major credit bureau.[24] This persists throughout the life cycle, as 93% of 50-year-olds have a credit file. Figure I considers the set of individuals with linked Census forms to study these patterns separately by racial group (Panel A) and

[23] Note that the Prolific sample is somewhat positively selected in terms of education and income, especially among Black respondents. See Appendix A.C for details. Nonetheless, results from the Prolific Survey are qualitatively similar to those from the other surveys.

[24] Note that, because our sample is limited to individuals with a verified PIK (see Section II), the true share of "invisibles" in the credit market could be slightly larger than what we estimate. Nonetheless, our estimates are broadly consistent with those from Brevoort, Grimm and Kambara (2015), who estimate an 11% share of credit invisibles by comparing counts of credit records to population counts from the 2010 Census.

parental income quintile (Panel B).[25] Black and Hispanic individuals obtain credit files at similar rates in their twenties but plateau at a slightly lower level in middle age: 95% of 35-year-old Black and Hispanic individuals have credit files in contrast to 97% of 35-year-old White and 96% of 35-year-old Asian individuals in 2020. AIAN individuals have the lowest age 35 match rates at 92%. When comparing across different levels of parental income, 93% of 35-year-olds whose parents were in the bottom quintile of the income distribution have a credit file at age 35 in 2020, in contrast to 98% for those whose parents were in the top quintile.[26]

Not everyone that has a credit file receives a credit score, as some files are too "thin" to be able to formulate a credit score. Appendix Figure A.2 reports the fraction of individuals who have a credit score. Among 35-year-olds in 2020 with linked Census forms, approximately 89% of AIAN individuals, 93% of Black, 93% of Hispanic, 95% of Asian, and 96% of White individuals have a credit score. For individuals whose parents were in the top quintile, 98% have a credit score by age 35, in contrast to 91% for those with parents in the bottom quintile of the parental income distribution. While we observe some modest differences in the fraction of people who obtain credit scores, we broadly conclude that over 90% of most subgroups of the adult U.S. population have a credit file and a credit score.

III.B Differences in Credit Scores

While we find modest differences in the fraction of people who have a credit file by one's background, we find large differences when examining the credit scores assigned to those credit files. The upper panel of Table I reports the average credit score by race for the population and intergenerational samples. We report the mean and median credit score, including a median score that imputes below median scores for those missing a credit score or file. In this section we focus on the intergenerational sample, though the results in the population sample are generally very similar.

The average credit score in 2020 for White individuals in our intergenerational sample is 701 in contrast to 601 for Black individuals—a gap of 100 points. Asian individuals have the highest credit score of any racial group in the U.S., with an average score of 741. The average scores for Hispanics and American Indian and Alaska Natives (AIAN) are 659 and 622, respectively, falling between those for Black and White individuals. We find broadly similar average credit scores for individuals in our population sample.

Among individuals with a credit score, we find that race gaps in median scores are larger than they are for mean scores. In our intergenerational sample, we find medians of 719 for White individuals, 581 for Black individuals, 781 for Asian individuals, 655 for Hispanic individuals, and 602 for AIAN individuals. We then extend our comparison of medians to include those without credit scores by assuming they have below-median scores. Gaps in median scores are similar after including these unscored individuals, even though median scores are mechanically lower for each racial group. White individuals have a median credit

[25] Appendix Figure A.1 reports these rates for other years (2004-2016). The fraction of people with credit files in the U.S. has increased slightly over time, but the broad patterns reinforce our interpretation of the patterns in Figure I as being a life cycle pattern. Note that the values in Figure I condition on individuals for whom we observe race.

[26] The fraction of people with a credit file does not vary much by parental education, with 93.9% of 25-year-olds in 2020 whose parents did not finish high school have a credit file, compared to 94.1% for 25-year-olds in 2020 with a parent who completed a bachelor's degree.

score of 712, in contrast to Black individuals with 571, Asian individuals with 776, Hispanic individuals with 644, and AIAN individuals with 583. In other words, we find a 140 point gap in median credit scores between White and Black individuals and a 205 point gap between Black and Asian individuals at ages 35-42.

The racial gaps we observe in Table I are larger than those identified in previous studies. Several papers have found racial credit score gaps between 10 and 60 points using HMDA data, which records both race and credit scores for mortgage applicants.[27] However, the set of borrowers who appear in HMDA are positively selected in terms of credit score because the population that applies for mortgages is a more creditworthy group than the general population. Indeed, Appendix Table A.1 reproduces the median credit score for the subset of people in our data with mortgages and generally finds higher scores and smaller racial gaps than in the full sample. For example, the Black-White gap in medians is closer to 79 points in this subsample, compared to a gap of 139 points in the full sample. More in line with our findings, Garon (2022) uses ZIP-code-level information on racial compositions to measure race gaps in credit scores, finding a median VantageScore gap of 105 points between 25 to 29 year-olds in majority Black and majority White ZIP codes. Similarly, Martinchek (2024) finds mean VantageScore gaps of 60-67 points among 20-29 year-olds in majority Black versus majority White ZIP codes. These raw gaps are qualitatively similar but slightly smaller than our main results, indicating that ZIP code imputation methods tend to attenuate measures of race gaps in credit scores.

The gaps in credit scores by race are remarkably similar across ages. Figure II Panel A reports the average credit score by age and race. Gaps in credit scores emerge early in life and persist throughout the life cycle. The average difference in credit scores between White and Black individuals is 97 points among 30-year-olds and 92 points among 60-year-olds. The fact that credit score gaps emerge at early ages and persist throughout the life cycle is useful in our exploration because we can only measure class and hometown for cohorts going back to 1978. These patterns provide some comfort that our comparisons across class and hometown focused on the 1978-85 cohorts can generalize beyond the particular cohorts and ages we observe in our linked data.

Turning to differences in credit scores by class, we find differences that are similar in magnitude to the differences we observe by race. The lower panel of Table I presents credit score gaps by parental income for our intergenerational sample. Individuals with parents in the bottom quintile of the parental income distribution have an average credit score of 630, in contrast to 740 for those from the top quintile. Similarly to the race gaps, Figure II Panel B shows that these gaps arise in one's early twenties and persist throughout the life cycle. Appendix Figure A.3 reports average credit scores by parental education level. We find an average credit score of 638 for those whose parents have less than a high school education, in contrast to

[27] Fuster et al. (2022) uses the subsample of individuals who have applied for mortgages and uses the HMDA filings to obtain race. They find median FICO scores of 774 for White non-Hispanic, 744 for Black and 775 for Asian borrowers. Similarly, Bhutta, Hizmo and Ringo (2024) find a Black-White FICO score gap of 41 points using a HMDA sample of purchase and refinance applications in 2018 and 2019 for first-lien, 30-year fixed-rate mortgages on owner-occupied single-unit homes for which an automated underwriting system recommendation was reported; Consumer Financial Protection Bureau Office of Research (2021) find Black-White credit score gaps of about 60 points on home mortgages in HMDA in 2018-2020; Bhutta and Hizmo (2021) find a Black-White FICO score gap of 13 points in a data set of 30-year fixed rate FHA home purchase loans originated in 2014 and 2015 with loan amounts under 625,000 and LTVs over 90%, for single-family, site built, owner-occupied properties; Gerardi, Lambie-Hanson and Willen (2021) find a Black-White VantageScore 3.0 gap of 51 points using HMDA data.

725 and 742 for those whose parents have a bachelor's or graduate degree, respectively. In short, gaps in credit scores by class have similar magnitudes as those by race.

Race and class each have an additive role in predicting gaps in credit scores. In Figure III, we plot the average credit score for children of different races against the child's parental income rank on the horizontal axis, measured using our intergenerational sample in 2020. Large racial gaps in credit scores persist conditional on parental income, albeit at an attenuated level. White children from the 25th percentile of the parental income distribution have credit scores that are 69 points higher than their Black counterparts, compared to an unconditional Black-White gap of 95 points. White individuals from the 25th percentile have an average credit score of 661 in contrast to 718 for those from the 75th percentile.

The slope of credit score and parental income is similar across all racial groups except for Asian individuals. We find high credit scores for Asian individuals whose parents have relatively low incomes, with an average of 732 even at the 25th percentile, which remains higher than the 695 average credit score of children in Black families whose parents are in the top 5%. It turns out that this pattern is largely attributable to the subset of first and second generation Asian immigrants in the U.S. Appendix Figure A.4 shows that when we restrict the sample to individuals who do not have immigrant mothers, the series for Asian individuals converges closely to the series for White individuals. In contrast, we continue to find lower credit scores for Black, Hispanic, and AIAN individuals relative to White individuals even when restricting to this non-immigrant subsample.

While we find large gaps in credit scores by race and class, we do not find significant gaps by sex. Table II reports credit scores by sex, broken out by race and parental income. Males tend to have credit scores that are nearly identical to females. This similarity in scores is notable in light of the sex gaps in income and intergenerational mobility documented by Chetty et al. (2020). For the rest of the paper, we mostly ignore this dimension of heterogeneity, as we do not find any meaningful differences in any of the future reported analyses if we were to report them by sex.

We also do not find large variation in gaps over time when measuring credit scores in other years of our data. Appendix Figure A.5 presents the patterns of average credit score by race and age using the 2004-2016 years of the credit data for the population sample. Appendix Figure A.6 presents the analogous comparisons for average credit scores by parental income quintile using the other years of credit data. We find some evidence that gaps by race and class emerge earlier in the life cycle – a pattern we return to below when discussing the rise of student loans – but the broad patterns of gaps are similar to those we find in 2020 presented in Figure II.

Next, we analyze variation in credit scores by one's hometown. Following Chetty et al. (2025), we map children to their childhood locations and study the heterogeneity in credit scores based on where people grew up, separately by race and parental income. We first construct a nonparametric regression of individual credit scores in 2020 (when individuals are 35-42 years old) on the individual's parental income rank at the national level. Then, for each county, we regress the child's credit score on an intercept and slope on the prediction given their parental income rank from the national regression.[28] For children who moved during

[28]For disclosure purposes, county-level outcomes are slightly shrunk towards the state-level mean in inverse proportion to the sample size, although we note this does not meaningfully impact the estimates.

childhood, we use a weighting strategy to assign them to counties in proportion to the number of years they spent in that county. We note that our results are very similar if we were to simply construct a linear regression of outcomes on parental income rank in each county, separately by race.

Our results reveal that variation in credit scores by hometown is roughly similar in magnitude to the variation by race and class. Table III takes the 100 largest counties in the U.S. and reports the top 10 and bottom 10 counties based on the average credit scores of those who grew up in each county, aggregating across race and parental income backgrounds. People who grew up in Bergen County, NJ have the highest credit scores on average, with a score of 724. This contrasts with those who grew up in Baltimore city who have an average score of 627.[29] We continue to find large gaps in credit scores even when we hold fixed race and parental income. Figure IV presents a map of the average credit score for White children with parental income at the 25th percentile of the income distribution. On average, White children who grew up in low-income families in Indianapolis, IN have a credit score of 629, in contrast to 719 for those who grew up in Brooklyn, NY and 694 in Minneapolis, MN. Broadly, the differences across hometowns are similar in magnitude to the gaps we observe by race and class.

Places with higher credit scores for White individuals tend to be places with higher credit scores for people of other races as well. Appendix Figure A.7 presents the maps of average credit scores for several other race and parental income groups. Average credit scores for Black and Hispanic children from low-income families have a correlation of 0.60 and 0.54, respectively, with those of White children from low-income families. Places where children from high income families grow up to have high credit scores also tend to be places where children from low-income families tend to have high credit scores (correlation of 0.91 among White children).[30]

In sum, the results demonstrate large differences in credit scores by race, class, and hometown. To put these numbers in perspective, lenders typically classify scores of 600 or below as "subprime," scores between 601 and 660 as "near prime," and scores above 660 as "prime."[31] The average credit scores among Black and AIAN individuals would therefore be classified as "near prime," as would those from the bottom quintile of the parental income distribution. In contrast, the average scores among White, Asian, and top-quintile individuals would be classified as prime. Strikingly, gaps in median scores imply that more than half of Black individuals are classified as subprime, while more than half of White individuals are classified as prime. Among White individuals from low-income (25th percentile) families, the average scores of those who grew up in Brooklyn, NY or Minneapolis, MN comfortably classify as prime, while the average scores of those who grew up in Indianapolis, IN classify as near prime.

These differences in credit rating likely lead to different borrowing costs on loan products whose prices are risk-based. For example, the average interest rate for new car loans among borrowers with near prime credit scores is 9.83%, compared to just 6.87% for prime borrowers (Zabritski, 2024). For a $20,000 auto loan with a term of 60 months, the difference between an interest rate of 9.83% versus 6.87% amounts to

[29]The city of Baltimore does not belong to any county and thus we treat it as its own county.

[30]One notable exception is Las Vegas, NV. Las Vegas is about an average place for children in low-income families but has some of the lowest scores relative to other counties for children from high income families.

[31]The full list of credit classifications and corresponding score ranges for VantageScore 4.0 are as follows: superprime 781-850, prime 661-780, near prime 601-660, subprime 300-600 (VantageScore Solutions, 2022).

paying an extra $28 per month and a total difference in interest paid of $1,708. Similarly, for personal loans, borrowers in the 690–719 range pay average interest rates of 12.5% to 15.5% while those below 629 pay average rates of 28.5% to 32.0% (Rivera, 2025). Thus, the score differences we observe impose both higher prices on risk-priced credit and tighter quantity constraints on products whose prices are effectively fixed.

III.C Balances and Evidence of Credit Constraints

Credit scores translate into borrowing capacity through underwriting rules that govern who can borrow, how much, and at what price. To test whether the score gaps documented above do in fact lead to credit constraints, we next study household balance sheets. We document six sets of empirical facts—spanning debt levels, account composition, utilization, timing of debt accumulation, inquiry behavior, and use of alternative financial services—that together point to binding credit constraints for groups with lower scores rather than weaker demand for credit. We present each fact in turn.

We first show that groups with lower credit scores have lower credit balances on average. Figure V Panel A shows variation in total debt balances in 2020 across races for our intergenerational sample. For each racial group, we present the average total debt held on their credit report in 2020, disaggregated by type of debt. Asian individuals have the highest balances at $190,500, followed by White individuals with $128,163 in loan balances. In line with their lower average credit scores, Hispanic, Black, and AIAN individuals have lower average balances of $91,084, $62,770, and $52,064, respectively. Figure V Panel C shows that, much like with credit scores, these differences in balances emerge early in the life cycle: in 2004 we observe balances of $14,171 and $13,674 for White and Asian individuals, in contrast to $10,920, $6,629 and $6,394 for Hispanic, Black, and AIAN individuals.

We see similar differences in debt balances by class. Figure V Panel B shows individuals in the bottom quintile of the parental income distribution have $66,820 in balances, in contrast to $184,890 for those whose parents were in the top quintile of the income distribution—patterns that broadly mirror the differences in credit scores for these groups. Appendix Figure A.8 presents similar patterns by parental education. Finally, Appendix Figure A.9 shows that differences in debt outcomes by race persist after conditioning on parental income. In all cases, the patterns align with the idea that individuals with lower credit scores face tighter borrowing constraints.

Second, we analyze the composition of household debt. In 2004, the composition of debt in our intergenerational sample is largely split across mortgages, auto loans, credit cards and student loans. But by 2020, when the sample is ages 35 to 42, mortgages become the largest component of debt for all groups. In 2020, Black and AIAN individuals held $32,720 and $31,990 on average in mortgage debt, respectively. In contrast, average 2020 mortgage balances are $66,430 for Hispanic, $100,900 for White, and $161,100 for Asian individuals.[32] Interestingly, the composition of debt by race is reversed for student loans, as Black individuals actually have higher student loan balances than any other racial group. This is consistent with the fact that most student loans are regulated by the federal government and are not underwritten using credit

[32] The lower auto and mortgage debts align with lower rates of homeownership and car ownership. Among 2015–2020 ACS respondents in our intergenerational sample with parents at the 25th percentile of household income, 89% of Black individuals owned cars and 41% owned houses, in contrast to 97% and 67% for White individuals.

scores. College enrollees of comparable financial need face the same borrowing terms on student loans, so we would not expect their balances to reflect the credit constraints they face in private credit markets.

Appendix Figure A.10 explores student debt in more detail and shows that this pattern is driven by an enormous rise in student debt loads for Black individuals, especially Black women, that emerged from 2004-2020. We also use data from the 1996 Beginning Postsecondary Survey to investigate the relative roles of initial borrowing amounts versus accumulated interest in explaining the different levels of student debt by race. Using a representative sample of student borrowers who entered college in 1996, Appendix Figure A.11 plots the average initial borrowing amounts along with the accumulated debt as of 2015 separately by race. While balances tend to decline over the life cycle for White, Asian, and Hispanic borrowers, we find that balances for Black individuals have increased, largely due to non-repayment of initial debts. We return to this pattern when discussing non-repayment in Section IV below.

We also find differences across hometowns in credit balances that broadly align with the credit score differences we observe. Credit card and mortgage balances are especially highly correlated with credit scores (correlation of 0.80 and 0.86), consistent with access to these tradelines being constrained by underwriting standards. The relationship between credit scores and auto loan balances is more nuanced. Across the U.S., there is no general relationship between credit scores and auto loan balances. But, Texas, which is an outlier in terms of its low credit scores and high auto balances, is arguably masking a positive relationship between auto balances and credit scores. Excluding Texas, we again find evidence of a positive relationship across counties in the U.S. between credit scores and auto balances. In contrast to these formal sector balances, we find a correlation of -0.24 between student debt balances and credit scores across hometowns. This is again consistent with student debt not being constrained by formal sector credit underwriting standards.

Third, we find that groups with lower credit scores have higher credit card utilization. Black and White individuals have roughly similar levels of credit card debt, but Appendix Table A.2 shows that Black and Hispanic individuals have much lower credit limits. Appendix Figure A.12 shows that their utilization rates are much higher than White and Asian individuals. This remains true even when we condition on income and past repayment.

Fourth, we find that the time path over which differences in credit balances emerge coincides with the time path over which gaps in the credit score emerge. Recall from Figure II that differences in credit scores emerge early in the life cycle. This suggests that it is important to zoom in on young adulthood to study what is happening at the entry points into the credit market and how these experiences vary by race and class. Figure VI plots the average number of tradelines by age, separately by race (Panel A) and parental income quintile (Panel B). People start entering the credit market in their late teens and early twenties, with large increases in tradelines at age 18 and 19. On average, individuals in 2020 have between 2-3 tradelines at age 21. However, the average number of tradelines diverges by race by roughly age 30 in 2020.[33]

What are the types of credit that initially bring people into the credit market? Appendix Figure A.13 plots the fraction of the population that has a tradeline by a given age on the horizontal axis, separately by race and the type of credit they received as their first tradeline. Appendix Figure A.14 does the same, but split out by class. Overall, most people obtain their first tradeline through a credit card, followed by

[33]The patterns by class are qualitatively similar, but the gaps are more pronounced.

a student loan. However, Black individuals in particular are more likely to have their first tradeline arise through a student loan. To be specific, among the 38% of White individuals in 2020 who have received a tradeline by age 20, 55% of these individuals' first tradeline is a credit card and 33% is a student loan. In contrast, among the 42% of Black individuals in 2020 who have received a tradeline by age 20, 32% of these individuals' first tradeline is a credit card and 56% is a student loan.

The rise of student loans as a primary source of first tradelines is a relatively recent phenomenon. In 2004, only 15% of White individuals and 19% of Black individuals with a tradeline by age 20 had a student loan as their first tradeline, in contrast to 33% and 56% in 2020. Alongside the rise of student loans, and perhaps as a result of them, we find that the Black-White gap in credit scores emerges slightly earlier in the life cycle in later cohorts where student loans are more likely to be present. Appendix Figure A.5 shows this by repeating the graph of credit score by age and race, as in Figure II, but measures the credit score in 2004–2016 instead of 2020. Our race gaps in credit scores are similar at age 40 in both 2004 and 2020, but the gap among 25-year-olds is wider in 2020. This is consistent with student loans leading to differences in credit scores that emerge early in the life cycle. It also suggests that the rise of student loans led to credit score gaps arising earlier in the life cycle but does not appear to have large long-run impacts on credit scores.

Fifth, we can explore how the demand for credit—as proxied by credit inquiries—varies by race and class at early ages in the life cycle. Although the number of tradelines evolves similarly by race and class prior to age 30, Black and low-income individuals have higher rates of credit inquiries. Figure VI Panels C shows that at age 25 in 2020, the average Black individual has 2.2 inquiries in contrast to 1.7 for the average White individual. Panel D shows that children from the bottom quintile of the parental income distribution have 2.0 inquiries at age 25 in contrast to 1.5 for those from the top quintile of the parental income distribution. This further reinforces our interpretation above that the lower balances for Black individuals and those from low-income families are not driven by lower credit demand, but rather by credit constraints.

Sixth, we present evidence that individuals in groups with lower credit scores are more likely to turn to alternative financial services. One of these is payday loans, which are measured in the SCF. Table IV reports results from a regression of payday loan usage on racial indicators, alternately using the full population and restricting to young individuals aged 22-30. Among all U.S. adults, 6.9% of Black individuals have used a payday loan in the last year, in contrast to 2.3% for White individuals.[34] This difference is similar among young adults aged 22-30, as 8.7% of Black individuals have used a payday loan and 3.0% of White individuals. Columns 3 and 4 show that these gaps persist even conditional on measured income, a pattern we return to below.

Summarizing our findings, we find large differences in credit scores and credit balances that emerge early in the life cycle. The evidence suggests that these gaps reflect differences in the supply of credit, as opposed to demand for credit. We focus the remainder of the paper on studying the determinants of these differences in access to credit.

[34] Formally, the question asks respondents whether they or anyone in their family living with them has taken out a payday loan in the past year.

IV Algorithmic Bias: Credit Scores versus Debt Repayment

A natural reason lenders restrict credit is the fear that they will not be repaid. Credit scores broadly aim to quantify the likelihood that individuals will repay debts. The analyses above suggest these scores disproportionately restrict access to credit for racial minorities, those from low-income and less educated backgrounds, and those from certain regions of the U.S. It is therefore natural to ask whether these differences in credit scores reflect bias on the part of credit scoring algorithms or true differences in the likelihood of debt repayment.

Credit bureaus are restricted in the type of information they can use to form credit scores. Inputs are limited to information in the credit file, including the number of accounts, balances, inquiries, and repayment history for various types of credit; public records, like bankruptcies and tax liens; and a log of accounts that have been sent to collections for non-payment. Race, income, address, and age are excluded. In this sense, credit scores are "race-blind" and cannot engage in "direct discrimination" in the language of Bohren, Hull and Imas (2022). However, there is growing recognition that seemingly neutral algorithms can generate unwarranted disparities (Barocas and Selbst, 2016; Kleinberg et al., 2018; Passi and Barocas, 2019; Obermeyer et al., 2019; Kiviat, 2019; Bohren, Hull and Imas, 2022; Black et al., 2022; Elzayn et al., 2025).

In order to measure algorithmic bias towards a racial group or class background, it is important to precisely define what one means by algorithmic bias. Kleinberg, Mullainathan and Raghavan (2016) summarize previous literature as offering two primary definitions: calibration and balance. These concepts capture two distinct notions of bias.[35] As we show, this distinction matters in practice.

Calibration A credit score is *calibrated* if rates of delinquency are the same between groups conditional on the credit score. To be precise, let $Y \in \{0,1\}$ denote a future delinquency outcome, let R denote one's group membership, and let S denote the credit score. Now consider the credit score's potential bias against either of two racial groups, $R = Black$ and $R = White$. The credit score is calibrated for Black and White groups if, conditional on any possible value of the credit score, s, future delinquency rates are equal between groups:

$$\Pr\{Y = 1|S = s, R = Black\} = \Pr\{Y = 1|S = s, R = White\}. \tag{1}$$

This definition is similar to notions of unbiasedness from Becker (1971) and subsequent empirical work using outcomes tests to detect bias in both algorithms and human decision-making (Obermeyer et al., 2019; Knowles, Persico and Todd, 2001; Simoiu, Corbett-Davies and Goel, 2017; Anwar and Fang, 2006; Benson, Li and Shue, 2023; Huang, Mayer and Miller, 2024; Arnold, Dobbie and Yang, 2018; Dobbie et al., 2021; Canay, Mogstad and Mountjoy, 2024).[36]

One way to think about our measure of calibration bias is that, under two assumptions, it studies

[35] An alternative definition of bias explores whether the algorithm would differ if it were estimated within racial group (e.g., see Avery, Brevoort and Canner (2012)).

[36] Our measure of calibration bias uses the outcome, Y, that is observed ex-post. If credit scores have a causal effect on repayment, these measurements may differ from those we would obtain by comparing latent potential repayment outcomes that individuals would realize in the absence of such score-treatment effects. We leave this as an important direction for future work.

the delinquency outcomes experienced by a lender who extends credit to someone with a credit score, $S = s$. First, assume that a borrower falls delinquent on the marginal offered loan if and only if they fall delinquent on some existing line of credit. This is perhaps more reasonable when considering small loans with negligible impacts on the delinquency outcome. Second, assume that the lender does not use any additional information or screening processes beyond the credit score. Under these two assumptions, $\Pr\{Y = 1|S = s, R = r\}$ measures the delinquency experienced by the lender by people of different groups, r. These two assumptions, of course, may not hold in practice. For example, someone offered a mortgage might continue to make their monthly payments even if they fall behind on their existing credit card in the future.[37] Additionally, a loan officer may combine the credit score with additional information when making a lending decision that could mitigate or amplify the biases we observe.[38] As a result, our measure of calibration bias provides a useful benchmark for understanding the credit scoring algorithm but may differ in practice from the biases that emerge in a particular lending decision.

Figure VII Panel A tests for the calibration of the credit score by race using our intergenerational sample in 2020. On the vertical axis, we plot the incidence of 90+ day delinquencies in the subsequent four years against the credit score on the horizontal axis, separately by race.[39] Before focusing on any bias in the score, note that the broad patterns are as one might expect: higher credit scores predict lower future delinquency rates for all racial groups. Delinquency rates fall from nearly one with credit scores below 500 to close to zero with credit scores above 800. However, the non-overlapping lines for each group reveal that the credit score is not calibrated by race: Black individuals have consistently higher delinquency rates than White and Asian individuals with the same credit score. Hispanic and AIAN individuals' delinquency rates fall between Black and White individuals. Among individuals with a credit score of 650 (in between the Black and White median credit scores in 2016), 61% of Black individuals have a 90+ day delinquency, in contrast to 47% for White, 39% for Asian, 52% for Hispanic, and 51% for AIAN individuals. This means that among those with a 650 credit score, Black borrowers are ~30% more likely to fall delinquent on their debts than White borrowers and ~50% more likely to fall delinquent than Asian borrowers. Appendix Figure A.16 shows that the calibration bias persists (and is even larger in percentage terms) when restricting the sample to borrowers without any late payments on their report in 2016. These results suggest that if credit scores were hypothetically modified to include the predictive information embodied in race but repayment patterns were held fixed, the Black-White gap in credit scores would rise from 100 points to ~130 points. This finding mirrors the conclusions of Fuster et al. (2022) who use HMDA data to argue that more predictive credit scores would disproportionately lower the credit scores of Black individuals.

We find a similar pattern when exploring patterns by class—as measured by either parental income or education level—and geography. Figure VII Panel B plots the incidence of 90+ day delinquencies against

[37]Our inability to observe delinquencies on loans that aren't offered is analogous to other settings where outcomes are only observed under certain decisions. For example, judges are supposed to make bail decisions based on defendants' potential pre-trial misconduct, which cannot be observed if they are detained.

[38]Closely related, Blattner and Nelson (2021) use variation in the supply of mortgages and find no evidence of calibration bias in this sample. This finding can be rationalized with ours if loan officers and mortgage companies use additional information or selection procedures that mitigate the population-level calibration bias that we document.

[39]The credit score generally aims to predict 90+ day delinquency in the subsequent two, not four, years. However, we obtain the same conclusions when re-defining our own credit score using a prediction of 90+ day delinquencies in the subsequent four years instead of two.

the credit score, separately by parental income group. Roughly 43% of those with a 650 credit score from top quintile families have a subsequent 90+ day delinquency, in contrast to 54% of those whose parental income is in the bottom quintile. Appendix Figure A.15 plots the incidence of 90+ day delinquencies against the credit score, separately by parental education. We find that 53% of people with a 650 credit score with parents who lack high school degrees have a subsequent 90+ day delinquency, in contrast to 43% of those for whom at least one parent has a bachelor's degree. Finally, among people with roughly a 650 credit score 55% of those who grow up in a bottom quintile repayment county have a subsequent 90+ day delinquency, compared to 43% of those who grow up in a top quintile repayment county. In short, credit scores systematically overestimate (underestimate) the repayment likelihood of those from disadvantaged (advantaged) groups.

Credit scores form a prediction of future delinquency using the history of information in the credit file. Assuming this information set grows with time, the predictive power of the credit score should increase as one ages. If true, this would lead to lower calibration bias at older as opposed to younger ages. To assess this hypothesis, Figure VIII shows how the calibration bias varies by age. We regress 90+ day delinquency (2016-2020) on the credit score in 2016 along with indicators of racial group Panel A) and parental income quintile (Panel B) using our population sample, separately by age. The figure then reports the coefficients at each age for Black, Hispanic, and Asian (White is the omitted category; we do not display the coefficient for AIAN due to sample sizes). Panel B reports the coefficients for quintiles 1, 2, 4, and 5, with the 3rd quintile as the omitted category.

In both panels, these results show that the credit score is less calibrated for younger ages when people are first obtaining credit. This is consistent with people having shorter credit files so that credit file information is relatively less predictive than one's socioeconomic background. Throughout their twenties as people build credit files, the predictive power of race conditional on the credit score declines while the observed gaps in credit scores expand. Intuitively, the repayment behaviors observed in the credit file start to capture some but not all information about one's likelihood of future delinquency that was contained in one's class and racial background. However, the credit score never perfectly incorporates this information, as the calibration bias stabilizes by age 30 and remains quite stable over the rest of the life cycle.

The above results evaluate the calibration of the credit score in relation to 90+ day delinquency in the subsequent four years. However, we find that our broad conclusions continue to hold for other race-blind scoring systems that one could use to forecast future non-repayment. For example, Appendix Figure A.17 evaluates the calibration bias for our own prediction of 90+ day delinquency measured in 2020 using the information in the 2016 credit file, showing that we find very similar patterns of calibration bias. We broadly find similar patterns using other measures of delinquency or non-repayment (e.g., 30+ day delinquencies, 60+ day delinquencies, collections indicators, amount past due, different follow-up time frames, etc.). We conclude that the calibration properties of the credit score that we observe are not unique to the VantageScore 4.0 or any other particular scoring method but rather reflect a fundamental property of the information contained in the credit file.

Balance A second definition of algorithmic bias is equal-odds or *balance* (Berk et al., 2017; Zafar et al., 2017; Bohren, Hull and Imas, 2022; Hardt, Price and Srebro, 2016; Chouldechova, 2017; Arnold, Dobbie and Hull, 2022). A credit score is balanced if it assigns similar scores on average to each group among those who ultimately have the same realized creditworthiness. To be precise, we condition on a particular repayment outcome, $Y = y$, and ask whether the algorithm assigned systematically different scores to different groups. Mathematically, for the case of racial bias between Black and White individuals, this corresponds to

$$E[S|Y = y, R = Black] = E[S|Y = y, R = White], \tag{2}$$

which can be evaluated within the set who repay on time $Y = 0$ and within the set who fall delinquent $Y = 1$. This definition has its roots in computer science and statistics and seeks to measure whether the errors of prediction algorithms vary by group.[40]

To assess potential balance bias in credit scores, we begin by comparing the average 2016 credit scores between individuals with no 90+ day delinquencies ($Y = 0$) from 2016 to 2020 in each racial group. Figure IX plots these race-specific average credit scores separately by age among the sample with no 90+ day delinquencies that occurred between 2016 and 2020. Panels A, C, and E present results by race, and Panels B, D, and F do so by parental income quintile. Restricting to individuals who have no 90+ day delinquency between 2016 and 2020 and averaging across all cohorts, Black individuals are assigned credit scores that are 70 points lower, and Hispanic individuals are assigned credit scores that are 39 points lower than White individuals (Panel A). In contrast, Asian individuals are assigned scores 9 points higher than White individuals. The balance bias against Black and Hispanic individuals grows throughout one's twenties and then stabilizes until around age 60. Panel C shows that we broadly find similar patterns when focusing on those who ultimately do fall delinquent on debt ($Y = 1$): White individuals on average received credit scores that were 40 points higher than Black individuals and 11 points higher than Hispanic individuals.

We find similar patterns when analyzing balance bias by class. Panel B shows that those from the bottom quintile who have no 90+ day delinquencies between 2016-2020 are assigned credit scores in 2016 that are 72 points lower than those from the top quintile of the parental income distribution. The balance bias for those who do not fall delinquent grows throughout their twenties, stabilizing by around age 30. Panel D shows that among delinquent individuals, those from bottom quintile families received credit scores that are 56 points lower on average than those from top quintile families. These results mean that within the set of people who do not make 90+ day late payments, those from groups that tend to be assigned lower credit scores on average have likely experienced worse terms in the credit market even conditional on their ultimate repayment outcome. What types of inputs into the credit score might generate balance bias? An analysis of this is beyond our scope, but credit scores are a function of (i) payment history, (ii) the fraction of the credit limit used, (iii) total balances, (iv) age and type of credit accounts, (v) number of recently opened accounts and credit inquiries, and (vi) amount of available credit (VantageScore Solutions, 2022). Therefore, members of disadvantaged groups with perfect repayment histories likely differ systematically

[40] We measure balance by conditioning on the observed repayment outcome, $Y = y$. If the score has a causal effect on the outcome, i.e., Y is a function of s, one might be interested in a bias measure that conditioned on the latent potential repayment outcome one would realize under a common hypothetical credit score (i.e., in the absence of score-treatment effects). As we note in Footnote 36, we leave the study of the causal effect of the score as an important direction for future work.

on these other dimensions.[41]

Our analysis of balance bias above considers a particular outcome for Y, namely the incidence of any 90+ day late payment between 2016 and 2020. For robustness, we consider an alternative measure of individuals' ex-post creditworthiness—the incidence of any late repayment on their credit report over an extended period. Figure IX plots the average 2012 credit scores among individuals with no recorded delinquencies between 1997 and 2020—a window that spans 15 years before and seven years after credit score assignment.[42] Within this set of "perfect repayment" individuals, we continue to find significant, albeit attenuated, differences in credit scores by race and class. Black individuals have an average credit score of 773 at age 35, in contrast to 788 for White individuals, 788 for Asian, and 779 for Hispanic individuals. These gaps are similar across the age distribution. These patterns suggest that from the perspective of a borrower who perfectly repays, it is difficult to escape their group-level differences in credit scores.

This finding that credit scores are calibrated against those from advantaged groups but biased from a balance perspective against those from disadvantaged groups highlights the importance of being clear about one's definition of "bias." It is known that it is not feasible to have an algorithm that satisfies both calibration and balance simultaneously (Kleinberg, Mullainathan and Raghavan, 2016). However, our results provide a case in which the ultimate conclusions about the direction of bias in the score depend on the framing of the question. Are White and Asian individuals less likely to fall delinquent than Black individuals with the same credit score? Yes. Among those who had perfect repayment of their debts, did Black and Hispanic people achieve this despite receiving lower credit scores along the way? Yes. Both of these "biases" are present in the data. Moreover, theory tells us that it is not feasible to remove these biases without removing the underlying group-level differences in delinquency.

Taking a step back, this also suggests that differences in delinquency rates are the fundamental driver of the large gaps in credit scores that we observe by one's background.[43] This naturally raises the question: what explains these differences in non-repayment across groups? We devote the remainder of the paper to studying this question.

V Life Cycle of Repayment and the Implications for the Role of Credit Terms

To understand the determinants of gaps in non-repayment, it is helpful to know (a) when in the life cycle these gaps emerge and (b) the types of credit products on which people are most likely to fall delinquent. Recall from Section 3 that credit scores and access diverge throughout one's twenties, and these group-level differences persist throughout the rest of the life cycle. It turns out that persistence in credit scores is not just present at the group level, but also within individuals over time. Using our intergenerational sample, we categorize individuals into credit score quintiles using their 2008 credit score. Figure XI then plots their

[41] Previous work documents that adding a child as an "authorized user" to a credit card on average increases the child's credit score (Bach et al., 2023). Appendix Figure A.18 shows that Black and Hispanic children are half as likely as White individuals to have these types of authorized user trades, consistent with this feature potentially contributing to balance bias.

[42] We can condition on repayment histories between 1997 and 2020 because 2004 credit reports retain delinquency records from the previous seven years.

[43] We see this clearly across hometowns as well in Figure X below, which compares childhood county-level credit scores and repayment rates for low-income White children.

average credit scores in the subsequent 12 years. While there is a small amount of mean reversion over time, the gap between those in the second and fourth quintiles of the credit score distribution in 2008 is 134 in 2008 and 122 in 2020. While credit scores generally increase with age, the relative position of someone's credit score changes very little between their late twenties and early forties.

Differences in delinquency emerge early in the life cycle, coinciding with early-life differences in credit scores. Figure XII shows that by age 25, 69% of Black individuals have a 90+ day late payment on their credit report, in contrast to 45% for Hispanic, 31% for White, and 17% for Asian individuals. Similarly, 60% of individuals from the bottom quintile of the parental income distribution have a 90+ day late payment at age 25, in contrast to 15% for those from the top quintile of the parental income distribution.

Most of these delinquencies arise from falling behind on credit cards, student loans, and other types of bills that have been sent to collections (e.g., phone or utility bills, medical bills, etc.). Appendix Figures A.19 presents the delinquency rates by tradeline. At age 25, 13% of Black individuals have fallen 90+ days behind on a student loan payment, 13% have fallen behind on a credit card, 37% have a non-medical collection and 24% have a medical collection. This contrasts with 5%, 7%, 11%, and 10% for White individuals on these tradelines. Delinquencies on auto loans and mortgages are much less common, reflecting the fact that these delinquencies emerge before most of these young adults enter the auto loan and mortgage markets.

The fact that non-repayment emerges early in the life cycle has important implications for the potential role of discrimination in the provision of credit in shaping non-repayment. In principle, discriminatory lending practices could lead to differences in terms of credit offers to different groups, which in turn could lead to differences in delinquencies. We do not observe the terms of debt contracts that individuals hold, but previous literature shows that the magnitude of discrimination varies by credit product. In mortgage and especially auto lending markets, there is evidence of racial discrimination. For example, Lanning (2021) finds that Black borrowers pay significantly higher interest rates on auto loans, and Butler, Mayer and Weston (2023) find that Black and Hispanic auto loan applicants' approval rates are 1.5 percentage points lower than those of White applicants, even after controlling for observable measures of creditworthiness.[44] Similarly, Bartlett et al. (2022) find that lenders charge Hispanic and Black borrowers 7.7 and 6.8 basis points more for purchase and refinance mortgages respectively, costing them at least $450M collectively per year in extra interest. In Appendix Table A.3, we replicate these findings of differences for auto and mortgage markets using data from the SCF. On average, even after conditioning on income, Black borrowers incur interest rates 2.33 percentage points above those of White borrowers for auto loans, and 0.66 points above for mortgages (Appendix Table A.3, columns 5 and 6).[45]

While there is evidence of potential discrimination in auto loan and mortgage markets where loan officers influence lending decisions, the vast majority of the delinquencies experienced by young adults occur on other bills that have little scope for loan officer discretion, limiting the potential for discrimination in credit offers. Many do not even depend on a measure of creditworthiness. Terms on phone and utility bills are generally standardized and do not depend on the credit score. Similarly, the terms of most student

[44]Cookson, Guttman-Kenney and Mullins (2025) find that immigrants obtain auto and mortgage loans at significantly lower rates, despite having better observable creditworthiness and similar credit card access as natives.

[45]Note that these gaps do not condition on credit scores (which are not available in the SCF), and are thus likely an overestimate of the gaps conditional on credit score.

loans are standardized by the government for all borrowers, regardless of creditworthiness. Credit card offerings are standardized and can vary by credit score, but we note above that delinquency patterns persist even conditional on the credit score, especially at young ages.[46] Because the gaps in delinquency emerge on products whose terms are standardized across groups, we conclude that discrimination in the offering of credit terms is not the fundamental driver of the repayment differences we observe in the data.[47] The key question is what explains the non-repayment outcomes that occur in one's twenties primarily on credit cards, student loans, and other bills that appear on the credit report when they are eventually sent to collections.

VI The Role of Income and Wealth

A natural explanation for differences in repayment is differences in income or wealth. We begin with an exploration of income, noting that there are well-known differences in income by race and parental income (Davis and Mazumder, 2018; Chetty et al., 2020). Here, we use the richness of our administrative tax data to explore the role of different current income, past and future income, and wealth in explaining differences in repayment. We focus both on explaining the overall differences in repayment across groups and the calibration bias that emerge conditional on credit score.

Motivated by the fact that non-repayment emerges early in the life cycle, we focus on the repayment patterns that emerge in one's twenties. Specifically, we use our intergenerational sample and focus on having a 90+ day delinquency between 2004 and 2008. Appendix Table A.4 presents the analogous results for our intergenerational sample when defining delinquency later in life, between 2016 and 2020, which yields conclusions that are qualitatively similar.

We begin by asking whether the gaps in 90+ day delinquency rates for young adults are explained by differences in early-life income (measured in 2004). Table V Panel A plots coefficients from a regression of the 90+ day delinquency indicator on measures of race (Black, Asian, and Hispanic indicators; White is the omitted category) and class (parental income rank). This specification allows us to simultaneously assess the race and parental income gaps, although we draw similar conclusions when analyzing them separately. Panel B reports the analogous specification when we also include controls for 2004 credit score rank, so that we focus on the impact of these controls on the calibration bias of the credit score. Without any income controls, the average Black-White gap in repayment in 2008 in the intergenerational sample is 27.24 percentage points, and the difference in repayment between the 1st and 100th parental income percentile is -45.79 percentage points. Panel B shows that conditional on the child's 2004 credit score, the Black-

[46] One concern is that credit cards may incorporate additional information beyond the credit score in their lending. However, Butler, Mayer and Weston (2023) do not find racial disparities in credit card lending, even among the same borrowers for whom they find racial disparities in auto loans. Appendix Figure A.20 replicates these patterns in the SCF and shows no difference in interest rates by race for credit cards. Indeed, in the SCF we find that Black borrowers pay slightly lower interest rates conditional on income and wealth.

[47] Conditional on the credit offered, there is evidence that different groups select different contracts. For example, Bhutta and Hizmo (2021) find that differences in mortgage interest rates between Black and White borrowers is explained by White borrowers choosing to pay more points to lower their interest rates. We note that differences in choices conditional on an offer set could in principle be driven by differences the supply of marketing or even predatory lending to different groups. We discuss the role of differential selection of credit products in contributing to differences in delinquencies in Section VIII when studying differential use of alternative financial services such as payday loans.

White gap is 13.36 percentage points and the parental income gap (top versus bottom percentile) is -19.54 percentage points. Panel B shows that race and class gaps are about half as large when we condition on credit score.

The second column includes controls for the child's household income rank in the base year before measuring delinquency (2004). This slightly reduces the Black-White gap in repayment from 27.24 percentage points to 24.90 percentage points and the parental income gap from -45.79 percentage points to -44.56 percentage points. Panel B shows that it also does not change the race gap or class gap in repayment conditional on credit score. This suggests that the fact the credit bureau does not observe income when forming credit scores is not a driver of the calibration bias in the credit scoring algorithm for young adults.

There are two reasons that income controls may not close the gaps in repayment. The first is that income shocks, not levels, may drive non-repayment. The second is that repayment decisions may be more tied to future lifetime income as opposed to income in young adulthood. For example, it may be more difficult to avoid wage garnishments or other collections attempts if one has a higher future income. Column 3 addresses both of these considerations by including a full vector of household income ranks in each year from 2003 to 2021. This means that we control for income both over the time frame during which we measure delinquency and also include *future* income as well, which can potentially affect incentives to repay. This reduces the impact of parental income by approximately one third, but only slightly attenuates the gaps in repayment by race. Panel B shows that these controls have virtually no effect on the calibration bias by race, but they do have a modest impact on the calibration bias by parental income. Overall, we find that differences in past, current, and future annual incomes do not explain the gaps in delinquency by race and class in our data.[48]

There are well-documented differences in wealth by race and class, even conditional on income (Darity Jr et al., 2018; Aliprantis, Carroll and Young, 2022; Thompson and Suarez, 2015; Derenoncourt et al., 2024), which can affect households' financial behaviors (Ganong et al., 2020). We provide two strategies to control for wealth. First, we construct proxies for lifetime measures of wealth on the full sample using information contained in administrative records. In particular, we observe: (i) deferred compensation as measured by Box 12 of the IRS W-2 tax form, cumulated over years 2005 to 2020, and (ii) housing wealth, which is the difference between the value of one's house and mortgage measured in 2016.[49] The race gaps are essentially unchanged by the addition of these controls, while the combination of future income and wealth remove roughly two thirds of the class gap. Our second strategy restricts to the subset of individuals who are observed in the SIPP in 2003-2004. Column 5 adds controls for (i) SIPP liquid assets, and (ii) SIPP net wealth. The race gaps are unchanged; the class gap is still significant, but attenuated to -15.02.[50]

One additional hypothesis is that the race and class gaps in repayment we observe are due to within-year

[48]We also control for individual income and find no meaningful impact on the estimates.

[49]We are not able to construct the housing wealth measures in the earlier years of our sample, so we instead focus here on controls for one's future wealth. A concern with this approach is that the early-life delinquencies may cause a reduction in later-life wealth; however, this would generally suggest we are over-controlling when including these wealth controls.

[50]Instead of controlling for the child's liquid and total wealth in the SIPP, we can alternatively restrict to the set of parents who are surveyed in the SIPP in 2003-2004 and control for parental wealth. On this sample, the black-white repayment gap is 18.48 percentage points, which falls to 15.61 percentage points after including controls for their liquid and total wealth. The gap conditional on credit scores falls from 9.48 percentage points to 8.06 percentage points after including liquid and total wealth controls.

fluctuations in income that could create liquidity constraints. We do not observe within-year fluctuations in income. However, to assess the potential role of such shocks, we restrict to the set of workers who are continuously employed at the same employer from 2005 to 2008 with their income rank in each year staying within 10% of their income rank in 2004. This has very little effect on race gaps in repayment, but it can also attenuate the class gap in repayment. Column 7 further shows the impact of adding employer fixed effects to this sample. We continue to find large race gaps and significant but muted class gaps in repayment, relative to specifications without controls for income and wealth.

Additionally, income and wealth also do not explain the geography of repayment across hometowns. For example, Figure X presents a comparison between the geography of non-repayment by hometown in Panel B for White individuals with below-median income parents alongside a map of the same repayment outcomes after residualizing on the individuals' income rank in 2016 (Panel D). We find a slight reduction in variance across places and a correlation of 0.95. Places with high repayment also have high repayment conditional on income.

To place these patterns in context and understand why these controls do not remove gaps by race in particular, it is helpful to compare the race gap in repayment to the relationship between own income and non-repayment. To do this, we focus on repayment between 2016 and 2020, when individuals are between ages 35-42 and thus their incomes better reflect a notion of permanent income. Column 2 of Table A.4 Panel A shows that, conditional on 2016 income rank and parental income rank, Black individuals are 21.2 percentage points less likely to repay than White individuals. The coefficient on own income rank in 2016 shows that going from the bottom to the top of the income distribution is associated with a 60 percentage point reduction in non-repayment. Thus, the Black-White repayment gap is roughly the same as the gap in repayment between individuals at the 33rd and 66th percentile of the income distribution, a difference of approximately $52,000 at ages 35-42.[51] Put this way, it is perhaps not surprising that controlling for income and wealth is unable to close a racial repayment gap that is roughly equivalent to a gap of $52,000 per year. Broadly, we conclude that income and wealth only partially explain the differences in repayment that we observe by race, class, and hometown.[52]

VII Childhood Influences

The fact that income and wealth do little to explain repayment is perhaps also not surprising when we consider that differences in income and wealth by race, class, and hometown emerge in one's thirties (Bhattacharya and Mazumder, 2011; Chetty et al., 2020), while the differences in repayment we observe emerge early in one's twenties. This early-life emergence of delinquencies suggests that perhaps factors from childhood could be shaping non-repayment outcomes in adulthood.

As a motivating exercise, we study whether the parent's credit score predicts repayment conditional on the child's credit score and measured incomes. Column 1 of Table VI presents the relationship between

[51]This value calculated by taking the difference between the 66th and 33rd percentile of the household income distribution among 35-42 year olds as measured using the 2016 ACS (using person weights).

[52]We also note our findings are consistent with Bartik et al. (2024), who show that randomly providing $1,000 per month for 3 years did not lead to a significant reduction in delinquencies.

having a 90+ day delinquency in young adulthood between 2004 and 2008 (when members of the intergenerational sample were between ages 19 and 26) and parental credit score (measured in ranks). The coefficient on parental credit score rank in 2004 is -0.751, implying that moving from the 1st to the 100th percentile of the parental credit score distribution is associated with a 75 percentage point decrease in the probability of having a 90+ day delinquency between 2004 and 2008.[53] Of course, some of this correlation may reflect the relationship between parental credit score and own income or own household balance sheet, so in Column 2 we add a control for income in 2004, but the coefficient on parental credit score rank is effectively unchanged. Income between ages 19-26 could be a poor proxy for one's actual financial circumstances and ability to repay debt. Therefore, in Column 3 we add a control for parental income rank while the child was between ages 13-17. Conditional on own and parental income, the coefficient drops only slightly to -0.577. In columns 4 and 5 we add controls for the child's wealth and parental education, and in column 6 we add controls for the parent's wealth and education; we continue to find a strong relationship between the parent's credit score in 2004 and child's subsequent repayment between 2004-2008, suggesting a channel of intergenerational transmission of repayment propensity that operates within the family.[54]

To further explore the potential role of childhood, we study whether the variation in repayment across hometowns is due to the causal effect of childhood exposure to those places.[55] Our ideal experiment would randomly assign children to neighborhoods and compare their outcomes in adulthood. We approximate this experiment using a childhood movers design following the methodology of Chetty and Hendren (2018*a*) and Chetty et al. (2020). This approach leverages variation in the age at which children move across counties to identify the causal effects of childhood exposure to a place on later-life outcomes. The key identification condition underlying this approach is not that families must move at random. Nor do we require when families move to be random. But, we require that the interaction of the child's age at move with the repayment characteristics of the destination location to be exogenous. In other words, we require no dynamic sorting of parents to places so that the time a child spends in a high versus low repayment place is uncorrelated with other determinants of a child's repayment outcomes (e.g., other parental inputs). This assumption could be violated in principle, but we present evidence below in support of this identification assumption.

To conduct this childhood movers analysis, we follow Chetty and Hendren (2018*a*) and split our sample into those who move across counties exactly once during our sample window and those who do not. For the non one-time movers, we construct the average outcome, $\bar{y}_{cps}$, for people who grew up in county c with parental income p_i in birth cohort s_i. We construct these separately for a range of credit outcomes, including

[53] See Hartley, Mazumder and Rajan (2019) for earlier work documenting the positive relationship between parental and child credit scores.

[54] In Appendix Table A.5 we replicate these findings for delinquency between 2016-2020 and condition on own income in 2016 rather than 2004. The relationship between parental credit score rank and own repayment is somewhat attenuated, but still remains quite strong: moving from the 1st to the 100th percentile of parental credit score distribution is associated with a 33 percentage point increase in delinquencies between ages 35-42, even conditional on own income, parental income, parental wealth, and parental education.

[55] To situate our approach in previous literature, we note that Keys, Mahoney and Yang (2023) use panel data on credit reports to show that debt delinquency rates vary significantly across areas of the U.S. Examining adults who move between areas, they show that repayment outcomes scarcely change after the move: roughly 90–95% of the cross-area dispersion is due to selection in who moves where, not post-move adaptation. We look earlier in life, linking the same geographic variation to individuals' hometowns and estimating how childhood exposure to a place shapes later repayment. In effect, we test whether the "selection effect" Keys, Mahoney and Yang (2023) observe in adulthood is forged during childhood and find that it is.

90+ day delinquency, credit score, and the residual after regressing 90+ day delinquency on income. We focus our attention in the main text on the 90+ day delinquency outcome, but broadly find nearly identical results when considering credit scores and income-residualized delinquency.

Next, we take the set of people who move once in childhood from origin county o to destination county d, and we estimate a regression of the following form:

$$\begin{aligned} y_i &= \sum_{m=-6}^{35} I(m_i = m)\beta_m \Delta_{odps} + \text{Controls} + \varepsilon_i \\ \text{Controls} &= \sum_{s=1978}^{1985} I(s_i = s)\left[\beta_s \Delta_{odps} + \zeta_s p_i + \alpha_s + \phi_s \bar{y}_{ops}\right] \\ &+ \sum_{m=-6}^{35} I(m_i = m)\left[\alpha_m + \phi_m \bar{y}_{ops} + \zeta_m p_i\right] \end{aligned} \tag{3}$$

where y_i is the credit outcome of interest, m_i is the child's age at the time of moving, $\Delta_{odps} = \bar{y}_{dps} - \bar{y}_{ops}$ is the difference in mean outcomes between the destination and origin counties for non one-time movers in cohort s with parental income rank p. The term $I(m_i = m)\beta_m \Delta_{odps}$ captures how much of the difference in mean outcomes between the origin o and destination d county is absorbed into the mover's adulthood outcomes for someone who makes such a move at age m. The controls capture cohort and age-at-move fixed effects, cohort- and age-specific parental income gradients, cohort- and age-specific selection on origin quality, and cohort-specific selection on destination quality. With these factors netted out, β_m is identified from comparisons of children who make the same origin-to-destination move at age m versus at adjacent ages, and the difference $\beta_{m-1} - \beta_m$ identifies the causal effect of spending age m in a location with a one unit higher predicted outcome, as measured by Δ_{odps}.

To accurately estimate equation (3), we need to account for the sampling variation in our estimates of Δ_{odps} and $\bar{y}_{ops}$ from the non one-time movers sample, as a standard OLS regression can lead to attenuation. Following Chetty et al. (2025), we split our sample of non one-time movers in half and use a split sample IV procedure, instrumenting the first subsample's estimates of Δ_{odps} and $\bar{y}_{ops}$ using those from the second subsample.[56]

Figure XIII Panel A presents the coefficients β_m for the outcome of whether the individual had a 90+ day delinquency between 2000 and 2004. An advantage of our analysis relative to previous research using the movers design is that we observe parental moves in our sample up to 7 years before the child is born. We find broadly stable coefficients around 0.8-0.9 prior to birth, providing a placebo test that there is no exposure effect on children prior to their birth. However, we observe exposure effects that emerge after birth and persist through the early twenties. The slope suggests that 1 year of exposure to a place with a 1 percentage point higher repayment rate causes the child to have a 0.02 percentage point higher repayment rate. We find no exposure effects after approximately age 23, consistent with no exposure effect after the repayment is measured in 2004 (when the average age of our sample is around 23).

Motivated by the shape of the patterns we observe, we also consider a parameterized specification that is identical to equation (3) but imposes that β_m can be approximated with a 3-piece linear spline with kink

[56] This leads to small increases in the magnitudes of our coefficients in our main specification of around 10%.

points at $m = 0$ and $m = 23$. Column 1 of Table VII presents the results using the 3 piece linear spline for β_m. We find no significant slope when $m < 0$ or $m > 23$, but find a slope of -0.019 for $m \in [0, 23]$, consistent with the patterns we observe. Comparing the pre-birth period to the post-outcome measurement period suggests roughly two-thirds of the variation in repayment reflects the causal effect of childhood exposure.

A key concern with the movers design is that families may dynamically sort to places in a manner that is correlated with outcomes in those places – in more informal terms: "good parents may be more likely to go to good places when their kids are young." Chetty and Hendren (2018*a*) provide several tests to address this concern using roughly the same sample of cohorts we study here to argue that this type of dynamic selection is not significant. We repeat their main test here using family fixed effects in Figure XIII Panel B. Adding family fixed effects to equation (3) yields a nearly identical pattern as the specification without family fixed effects in Panel A. Column 2 of Table VII shows that we obtain a slope of -0.015 (s.e. 0.003) in the linear spline specification. Figure XIII Panel B shows that the nonparametric slope for this specification is -0.018 (s.e. 0.002). Broadly, we find no evidence of dynamic selection and conclude that the geographic variation in credit outcomes largely reflects the causal effect of childhood exposure to these places.

Our baseline analyses in equation (3) measure Δ_{odps} separately by parental income but not by race. We can also consider a specification that estimates Δ_{odps} separately by racial group. In doing so, we further include interactions with race for origin outcomes, $\bar{y}_{ops}$, parental income, p_i, cohort, s_i, and age at move, m_i, to ensure we are identifying β_m from children who move at different ages as opposed to correlations between other race-specific determinants of one's outcome and the ages at which one moves as a child. Column 3 presents the results from this specification using the 3-piece linear spline and finds similar effects.

An advantage of computing Δ_{odps} separately by race is that we can test whether place has a race-specific effect on individuals. To do so, we include a placebo control for the exposure effect prediction for people of a different race. In Column 4 we restrict our sample to Black and White individuals and include values of $\bar{y}_{ops}$ and Δ_{odps} separately for one's own race and the other race. We estimate a slope coefficient on one's own race of -0.024, similar to what we found previously when pooling races, and a slope of 0.002 for the other race, which is not statistically different from zero. In other words, if a White and a Black person grew up in a place with a smaller racial gap in repayment outcomes, the gap between their outcomes would on average be smaller in proportion to their exposure to that place. In this sense, the results are consistent with childhood environments shaping not only the differences across hometowns but also the gaps by race as well. In short, one's childhood environment appears to be a key pathway for why one's background influences their repayment outcomes and access to credit in adulthood.

VIII Potential Mechanisms

How might one's hometown have a causal effect on their repayment? One clue is that places that tend to promote debt repayment also tend to promote upward income mobility. Figure X Panel B presents a county-level map of repayment outcomes for White individuals who grew up in below-median income (25th percentile) families. For comparison, Panel C presents a county-level map of average incomes of children growing up in below-median income families from the Opportunity Atlas. The correlation between county-level repayment and county-level income among below-median White families is 0.81.

One natural explanation for this correlation could be that higher rates of debt repayment in certain places are a causal consequence of higher incomes among individuals growing up in those areas. However, the patterns above suggest the story is more nuanced. Controlling for income does not remove the differences in repayment, especially early in the life cycle. Moreover, the map in Figure X shows that we find a strong correlation between counties that promote higher incomes and counties that promote debt repayment *conditional on income* (Panel D). This pattern is more consistent with a model in which upward income mobility and debt repayment share a common latent factor than one in which higher income mobility leads to higher repayment.

To help understand what factors, social processes, or institutions might generate these childhood exposure effects that shape repayment in adulthood, we turn our focus to a range of potential mechanisms suggested by the existing literature in sociology and economics. We begin with the role of financial literacy.

VIII.A Financial Literacy and Information

A large body of work has documented the role of financial literacy and education in shaping a range of financial decisions (Hilgert, Hogarth and Beverly, 2003; Lusardi and Mitchell, 2014, 2023). Much of this work has studied the variation in people's responses to the "Big 3" questions regarding financial literacy:

1. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? [Possible answers: more than $102, exactly $102, less than $102]

2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? [Possible answers: more than/less than/same as today]

3. Buying a single company's stock usually provides a safer return than a stock mutual fund. [Possible answers: true/false]

Previous literature has also documented that young adults in particular tend to score lower on measures of financial literacy. On average, 33% of U.S. adults correctly answer all three questions in the SCF, while young adults aged 22-30 correctly answer all three questions 26% of the time. Previous literature has also documented that rates of correct answers to the Big 3 questions vary by one's race.[57] We replicate these patterns for young adults in particular in the SCF: Black young adults are 42% less likely than White young adults to answer all three questions correctly. We also find variation in rates of correctly answering all three questions across U.S. states using data from the NFCS, shown in the map in Appendix Figure A.21. We find a state-level correlation of 0.77 with both our measures of repayment and repayment conditional on income. Places that promote repayment tend to also be places where people score more highly on these measures of financial literacy.

[57] See also (Barton and Rodet, 2025) who document variation in financial literacy by demographic characteristics using 15 survey questions.

People who correctly respond to financial literacy questions are less likely to fall delinquent. Table VIII presents a regression of self-reported delinquency[58] in the SCF against responses to the Big 3 financial literacy questions, focusing on young adults aged 22-30. People who correctly answer the inflation question are 10.8 percentage points less likely to fall delinquent. We find no meaningful difference for those who correctly understand compounding interest or stock market diversification, although we note that these are all coarse and highly correlated variables with an F-test on all three rejecting the null of no effect with $p = 0.000$. Although financial literacy measures are strongly correlated with an individual's income and wealth, we continue to find strong correlations when controlling for household income (Column 2) and wealth (Column 3).

Columns 4 and 5 provide suggestive evidence on whether financial literacy may be mediating the repayment gaps we observe. The SCF does not provide information on class or geography, but it does provide information on race. Column 4 shows that Black individuals are 18.5 percentage points more likely to report being delinquent on a loan than White individuals; and Hispanic individuals are 3.5 percentage points more likely to report being delinquent, though the latter difference is not statistically significant. Column 5 then adds controls for the Big 3 financial literacy variables. We see that they continue to strongly predict repayment conditional on race. But they have only a small impact on the race gap in repayment conditional on income (18.5 percentage points vs 17.7 percentage points for Black; 3.5 percentage points versus 3.3 percentage points for Hispanic).

While the Big 3 questions shed light on the role of overall financial literacy, it could be that what matters is particular knowledge about how the credit scoring and credit bureau systems work (i.e., the impact of non-repayment). To that aim, we asked individuals in our Prolific survey a more direct question about the credit reporting system, namely how long late payments stay on one's credit report. Appendix Table A.6 shows that Black individuals and those from areas of the U.S. with lower credit scores and higher non-repayment tend to think payments stay on the report for less time than White individuals and those who grew up in areas of the U.S. with higher debt repayment rates.[59] Interestingly, we find the opposite when studying patterns by class: those whose parents are more educated are less likely to know how long late payments stay on a credit report, perhaps because they have less experience with late payments or because their parents insulate them from the need to understand the inner workings of the credit market.

To assess the impact of controlling for this knowledge on having a missed payment, Column 3 first reports the results from a regression of having a self-reported missed payment in the last year on the measures of race, class, and hometown in our survey – namely, an indicator for Black, the number of parental years of education, and the non-delinquency rate of one's hometown based on their reported childhood county. Reassuringly, we find that people's self-reported missed payments follow the patterns we observe by race, class, and hometown. Black individuals are 11.1 percentage points more likely to have missed a payment, those whose parents have one more year of education are 1.4 percentage points less likely to have missed a payment, and those who grew up in a county with a 1 percentage point lower delinquency rate are 0.449

[58] The exact question asked by the SCF is "Now thinking of all the various loan or mortgage payments you made during the last year, were all the payments made the way they were scheduled, or were payments on any of the loans sometimes made later or missed?"

[59] The correct answer is seven years.

percentage points less likely to have missed a payment. These patterns are muted relative to what we observe in the administrative data, which could be due to incorrect self-reports or non-random sampling of Prolific. Keeping this caveat in mind, Column 4 adds controls for their belief about how long late payments stay on a credit report and an indicator for whether they report the correct duration. These controls are predictive of non-repayment but have only a modest impact on the relationship between race, class, and hometown and having missed a payment. The coefficient on Black drops from 0.111 to 0.098, and the coefficient on parental years of education drops from -0.014 to -0.009, while the coefficient on the county-level repayment rate actually rises from -0.449 to -0.516.

In short, our evidence that measures of financial literacy tend to correlate with measures of race, class, and hometown is consistent with previous literature. We find more modest and mixed evidence that these particular measures meaningfully explain the repayment gaps we observe. We note that our measures of financial literacy are, of course, imperfect, so that our results may not generalize to richer measures of one's financial literacy.

VIII.B Economic Instability

Another mechanism that could explain the differences in repayment we observe is differences in economic instability (McCloud and Dwyer, 2011; Morduch et al., 2019). While we ruled out income and income shocks, less advantaged Americans may be more exposed to instability or expenditure shocks if persistent poverty leaves them less able to invest in higher quality durable goods (Eisfeldt and Rampini, 2007; Yurko, 2008), take advantage of bulk discounts (Bauner and Hossain, 2023), purchase insurance (Gropper and Kuhnen, 2025), go to college (DeLuca et al., 2021), or find high-quality and stable housing (Desmond, 2017). Indeed, traditional measures of life stability, such as the fraction of children in two-parent households, have some of the strongest correlations with both upward mobility and non-repayment in Figure XIV.

To better understand the potential role of financial instability, we asked respondents in our Prolific survey about a range of unexpected expenses, including auto or home repair, medical or legal expenses, childcare or utility bills, or moving costs. Appendix Figure A.22 presents the correlations with our measures of race, class, and hometown. Broadly, we find some small differences in shocks to private consumption expenditures by race.[60] Black individuals are 5.2 percentage points more likely to have an unexpected childcare or school expense and 4.8 percentage points more likely to have a ticket, fine, or legal expense (in line with work by Harris (2016)). We find no significant differences across hometowns. People whose parents have less education are actually less likely to report having auto and home expenses, perhaps due to lower rates of car and home ownership, and are more likely to report having had no unexpected expenses in the last three months.[61] Adding a vector of controls for all types of unexpected private expenses in Appendix Figure A.22 to a regression of delinquency on an indicator for being Black, parental education,

[60]The one large difference we observe is differences in unexpected payments to family and friends. We exclude this from our measure of private expenditures and return to this measure in the social capital section below.

[61]The SCF asks respondents about the incidence of receipt and payment of child support and alimony. 6.1% of Black respondents report paying child support or alimony and 5.8% report receiving child support or alimony, in contrast to 3.8% and 3.4% for White respondents, 5.3% and 5.7% of Hispanic respondents, and 1.1% and 2.6% of Asian respondents. However, controlling for both payment and receipt of child support/alimony, and amounts thereof, has essentially no effect on racial gaps in repayment.

and childhood county repayment rate reduces the race gap in repayment from 0.11 to 0.10. Broadly, it appears that there is some evidence for differences in expenditure shocks, but it does not meaningfully explain the repayment gaps we observe.

VIII.C Social Capital

While private expenditure shocks do not explain the missed payment patterns, another hypothesis is that the variation in delinquency by race, class, and hometown reflects differences in the ability of people to deal with and manage the shocks that occur in one's life. There are large strands of work in both economics and sociology that discuss the ability of one's social ties to offset disadvantages and confer advantages through the provision and exchange of financial resources. Indeed, the importance of informal insurance networks dates to foundational work in economics (e.g., Townsend (1994)) and sociology (e.g., Coleman (1988)), both strands of literature highlighting the potential benefits and costs of sustaining such networks. Beyond direct financial exchange benefits, both economics and sociology have recognized the key role one's family, community, and broader network can play in providing information, strategies, and norms (Bourdieu, 1986; Jackson et al., 2008; Mobius and Rosenblat, 2014; Portes, 2024).

As some motivation for the role of social capital, Figure XIV shows that one of the strongest correlates of delinquency is one particular measure of social capital – namely "economic connectedness", which is defined as the fraction of below-median SES children's friends who are above-median SES (Chetty et al., 2022). Places where low-income children have more high-income friends are places where those children tend to grow up to be less likely to fall delinquent. From a theoretical standpoint, the composition of your social network determines what it can do for your economic prospects because of the nature and amount of the various resources they can provide. Some scholars argue that even a strong same class or same race/ethnic network can be helpful for survival (Stack, 1974; Dominguez and Watkins, 2003) and mobility (Light, 1984; Portes, 1995; Putnam, 2016), while others point out their potential limitations. For example, your closest network members can depress mobility because they are information redundant (Granovetter, 1973), disconnected from beneficial institutions (Loury, 1977; Wilson, 1996), or a source of additional financial obligations (Chiteji and Hamilton, 2002). In a connected community, having more peers facing financial difficulties can in principle be a source of financial instability for oneself.

VIII.C.I Social Capital as Informal Insurance

To assess the potential importance of one's informal financial network, we asked respondents in our Prolific survey how many times their family/friends had asked them for money, how much they gave, and how much money they could borrow from friends and family. Black young adults were asked for financial help 1.9 more times in the last 3 years than White young adults; they are 39% more likely to have given such financial help. Most of this is driven by a higher likelihood of giving to a sibling (42% vs 9%) and a parent (21% vs 18%). Table IX Columns 1-3 show that we also find similar patterns when regressing these measures on our three measures of background: race, class, and hometown. We find strong evidence that Black respondents and those from lower repayment hometowns give financial assistance more often, give greater amounts of financial assistance, are asked for financial help more often, and are less able to borrow. By contrast, those whose parents have lower education levels give less and are asked for financial help less often. We find corroborating evidence of these patterns in the SCF as well: Black young adults are more likely than White young adults to give financial support to family and friends, conditional on income.

Given the greater presence of financial payments to family/friends, one might have thought that Black individuals may also be on the receiving end of these transfers, so that they can receive greater financial support when in need. However, this is not the case. Black young adults report being able to borrow \$443 less from family/friends in our Prolific Survey. This is documented in Column 4 of Table IX, which shows that Black respondents, those with low parental education, and those from low repayment hometowns are all less able to borrow. In the SCF, Black young adults report being 39% less likely to be able to borrow \$3,000 from family and friends if needed, as compared to White young adults. In the PSID, we find Black young adults are 36% less likely to receive transfers from family (those from low parental education households are 49% less likely; those from below median repayment home states are 23% less likely), receive help in fewer months per year, and receive smaller amounts.

It might seem counterintuitive that Black young adults are both less likely to receive help from family/friends and more likely to pay money to family/friends, as this suggests that there is a net outflow of payments from Black young adults relative to White young adults in general. One rationalization of this fact is that Black young adults are significantly more likely to support their parents and less likely to receive transfers from their parents. In the SCF, when focusing on all ages, Black individuals are 23% less likely to give money to children over age 18 and 109% more likely to give money to their parents. Broadly, this suggests that intergenerational transfers are relatively more likely to flow upstream from young to old in Black households as opposed to from old to young in White households, perhaps due to differences in generational wealth that we did not capture in our SIPP measurement of wealth. Taken together, this suggests that Black young adults face a greater degree of financial burdens from family and friends (siblings in particular) combined with a lower likelihood of financial resources flowing to them from older family members.[62]

Do these differences in informal insurance obligations and parental obligations correlate with non-repayment? We ask individuals in our Prolific survey if they are behind on a debt payment or bill, and 53% report being behind on a bill or loan. These self-reported delinquency measures are slightly lower than the credit bureau data, though qualitatively similar.[63] Table X presents results from a regression of non-repayment on an indicator for being Black, parental education as a proxy for class, and the county-level repayment rate. The first column shows that in general we replicate the qualitative patterns in the administrative data of greater non-repayment for Black individuals, those with less educated parents, and those from counties with a lower repayment rate.

[62] We note these patterns are consistent with community-level wealth having an effect on economic outcomes as discussed in Chiteji and Hamilton (2002) and Bayer, Charles and Park (2025). There is also a literature in sociology that documents that Black children and youth may take on roles in their families that are parent-like in nature, and "assume extensive adult roles and responsibilities within their family networks" (Burton, 2007).

[63] Only 17% of SCF respondents (and 24% of respondents aged 22-30) report a missed payment, though the SCF asks respondents about “all the various loan or mortgage payments you made during the last year” whereas our Prolific survey asked “In the past year, have you ever missed a payment on a credit card, car loan, student loan, or other type of debt/money you have borrowed?” so it is possible that some SCF respondents failed to report missed credit card or other types of payments.

We then assess the impact of controlling for transfers to family and friends. The second column introduces controls for the amount of financial assistance the individual has given and the frequency with which they gave financial assistance. This reduces the Black-White race gap by about one-third, as giving financial assistance is associated with non-repayment and Black young adults are more likely to give financial assistance than White young adults. The third column adds controls for the number of times in the past three years an individual was asked for help with money by family and friends, the fourth adds the amount they think they could borrow from family and friends in an emergency, and the fifth includes both the number of times they were asked for financial help and the amount they think they could borrow. Including these controls, we find that the key drivers of non-repayment are the number of times they were asked and the amount they could borrow from family/friends. This suggests that the key variables explaining non-repayment and the various gaps in our data are not the exact quantities paid by these individuals but rather their ability to obtain resources from people in their network and the overall demand for credit (or insurance) from others in their network.

In addition to these findings in our Prolific survey, we find qualitatively similar patterns in the SCF. Simply controlling for an indicator of whether or not someone gave financial support to others and an indicator for whether they think they could borrow $3,000 from friends or family reduces the Black-White gap by 21%. In other words, controlling for these two variables has a similar effect on the race gaps in early life delinquency as controlling for a decade of tax return information. While these social network variables have predictive power for repayment, these variables could also simply be a symptom not a cause of non-repayment. It could be, for example, that everyone in your environment (including yourself) is credit constrained, leading everyone to ask each other for money and have lower ability to receive money from their network. Broadly, these patterns suggest a valuable direction for future work is to uncover not only the underlying causes of non-repayment but also how these conditions or practices operate across one's social and family network.[64]

VIII.C.II Social Capital as Cultural Capital

Another way social capital can be valuable is in the creation of knowledge about how to effectively navigate complex decisions and situations. This perhaps relates more closely to the literature on 'weak ties', beginning with Granovetter (1973) and later Burt (2003), who argued that weak ties are more likely to help you get ahead with job leads and in terms of economic mobility because, "those to whom we are weakly tied are more likely to move in circles different from our own and will thus have access to information different from that which we receive" (Granovetter, 1973). Thus, it is also possible that economic connectedness can be valuable for low-income individuals because higher SES networks might provide resources and the kinds of cultural capital or practices that help you not only gain financial literacy and learn why repayment matters,

[64] It is also possible that, in addition to the frequent financial requests from one's networks and the inability to borrow from them when needed, people are forced to make difficult choices between paying for their credit cards and paying for other pressing bills or needs, like utility bills or children's school expenses. A growing literature in sociology sheds light on these constrained financial decisions, including how people prioritize some expenses and purchases over others (Zelizer, 2004). For example, some families alternate between paying different bills in a given month, and others consider different types of debt more or less important to pay depending on whether they feel they were "duped" into it (Tach and Greene, 2014). Additional work shows that some low-income families both prioritize paying off debt and increase consumption when they receive their EITC payments (Sykes et al., 2015).

but learn how to enact behaviors and navigate financial institutions and learn the seemingly hidden rules of the game for how to anticipate and avoid difficult financial situations. Indeed, this could be part of the reason the parental credit score is so predictive of a child's repayment in young adulthood even conditional on parental and child financial resources.

There is a large literature in economics and sociology documenting that the way people deal with economic shocks, constraints, and difficult decisions can differ depending on one's background and earlier-life experiences. For example, DeLuca, Wood and Rosenblatt (2019) show that because poor families rarely decide to move—and instead move in reaction to unpredictable adverse circumstances—they engage in "survival" thinking and tried and true strategies to quickly secure *shelter*, rather than the time consuming forward-looking investment thinking that might lead them to move to higher opportunity *neighborhoods* (see also Harvey et al. (2020)). More generally, when facing uncertain and new difficult situations, individuals often fall back on their past experiences and "toolkits" to help navigate a complex environment (Kahneman, 2011; Mullainathan and Shafir, 2013; Swidler, 1986). Loosely related, there is a literature in anthropology and evolutionary biology documenting how humans learn from their social environment about how to deal with difficult questions and situations (Henrich, 2015). Given that people's early environments can differ significantly in terms of relative advantages and resources, what they learn can differ in consequential ways when dealing with institutions as they grow up, such as financial institutions. Such decisions multiply in frequency, complexity and variations at the transition to adulthood, when people are deciding where to live, whether to go to school, whether to partner and start a family (Settersten Jr., Furstenberg and Rumbaut, 2005; Arnett, 2014).

Recent work has also highlighted the particular difficulties faced when managing the student loan system in the U.S., which poses a particular set of obstacles for young borrowers. A complicated web of loan types, repayment plans, and forgiveness programs often lead students to make suboptimal borrowing and repayment decisions. For example, in the face of an economic shock or difficulty repaying student debt, borrowers often file for forbearance, fall delinquent, or even default on their student loans when they are eligible for zero-dollar payments under income-driven repayment plans (Herbst, 2023; Looney and Yannelis, 2015; Mueller and Yannelis, 2022). Experimental studies find that these sub-optimal decisions are sensitive to behavioral nudges, informational interventions, or alternative framings (Cox, Kreisman and Dynarski, 2020; Abraham et al., 2020; Kuan et al., 2025; Marx and Turner, 2019, 2020), suggesting that poor financial decisions may reflect a lack of guidance on how to navigate complex systems.

Another place where borrowers may be making financial decisions shaped by their environments as opposed to perfect knowledge of the benefits and costs is in the reliance on alternative financial services, such as payday loans and pawn shops. In general, use of these services does not appear on credit reports. There is a large debate in the existing literature about the pros and cons of these types of credit (Caskey, 1994*a*; Stegman and Faris, 2003). Proponents contend that payday loans provide vital short-term liquidity to individuals facing unexpected expenses, enabling them to smooth consumption and avoid costly overdraft fees or late payments (Zaki, 2013; Morgan, Strain and Seblani, 2012). Critics, however, emphasize that the extremely high effective interest rates and frequent rollover features of payday loans can trap consumers in cycles of debt, exacerbating financial distress rather than alleviating it (Graves, 2003; Smith, Smith and

Wackes, 2008; Skiba and Tobacman, 2011; Morse, 2011; Melzer, 2011; Faber, 2018, 2019; Small et al., 2021). Moreover, field and policy experiments that inform individuals about the cost of payday loans relative to other products have found significant reductions in payday loan usage (Bertrand and Morse, 2011; Wang and Burke, 2022), consistent with demand for these products being driven in part by learned behavior rather than fully-informed optimization. Similarly, pawn shops offer collateralized loans with minimal credit requirements and immediate cash, serving as a lender of last resort for underserved households (Carter and Skiba, 2012). Yet individuals risk forfeiting valuable items and face steep fees when redemption is delayed, raising concerns about welfare losses and regressive impacts on low-income consumers (Caskey, 1994*b*).

In Section III.C, we already documented that Black individuals are more likely to utilize payday loans. Here, we expand on this using our Prolific survey to study usage of additional forms of alternative financial services and to study variation by parental background and hometown. We asked respondents if they had ever used a range of forms of alternative financial services, including payday loans (storefront or online), auto title loans, pawn shops, BNPL arrangements, and rent-to-own. Table XI Panel A shows how usage of these alternative financial services varies by race, class and hometown by regressing an indicator for use of each of these services on an indicator for being Black, parental education, and the delinquency rate of their hometown. Those who grew up in places with greater non-repayment are more likely to use pawn shops, but not more likely to use payday loans. In contrast, Black individuals are relatively more likely to use payday loans than pawn shops. Pawn shops are generally considered to offer better financial terms than payday loans (Carter and Skiba, 2012), suggesting that Black individuals are more likely to find themselves in situations requiring a loan but not having the collateral to provide to a pawn shop.

Panel B presents the results from regressing non-repayment on these same race, class, and hometown variables along with controls for whether the individual has ever used various alternative financial services. After controlling for these factors, we find no evidence of repayment gaps by race, class, or hometown. This attenuation could reflect the potential adverse effects of predatory payday lending to Black individuals. Alternatively, the heavy use of payday lending among delinquent Black individuals could be a symptom of credit constraints rather than a cause of non-repayment.[65]

While we cannot discern whether these correlations reflect a causal effect of alternative financial services, our survey results do rule out some potential theories. In particular, the fact that delinquent Black individuals are turning to payday loans suggests their delinquencies are not the result of inattention or strategic default.[66] Rather, our results speak to the financial distress and credit constraints faced by many households from disadvantaged groups.

[65] We also caution that Bhutta, Skiba and Tobacman (2015) find that access to payday loans does not affect credit scores or formal sector credit access. Our results above do not reject this interpretation, but our broader findings raise questions about potential longer-run exposure effects. Perhaps once an individual is exposed to alternative financial services, their behavior and management of money cannot be affected. But, if their children were not exposed to these alternative forms of credit, they would avoid them when they become adults.

[66] We also used the linked SIPP data to search for evidence of strategic default by comparing liquid wealth in one's bank account to the amount past due reported in the credit file. We generally find low liquid wealth that is not enough to cover the outstanding balances due.

IX Conclusion

We provide new measures of differences in access to credit by race, class, and hometown and discuss several underlying determinants of these gaps.

We find large differences in credit access and that credit scores understate the true differences in repayment by class, race, and hometown. This suggests there is no easy change to the credit scoring system that would reduce barriers in access to credit. Indeed, more accurate (i.e., calibrated) credit scores would likely exacerbate these gaps in credit access. Expanding the credit scoring system's access to alternative measures of repayment on other financial products like payday loans could increase credit access for some, but would also likely expand racial gaps in credit scores.

Our results suggest focusing on credit-management habits developed during childhood. As suggestive evidence of intergenerational transmission of financial habits, a parent's credit score remains a powerful predictor of a child's own repayment record, even conditional on income and wealth. In addition, the movers design shows that children who spend more of their formative years in counties with higher repayment rates are significantly less likely to miss payments as adults, even at identical adult earnings. This pattern aligns with previous literature that finds larger effects on delinquency from variation in one's childhood neighborhood as opposed to one's contemporaneous neighborhood (Miller and Soo, 2021; Keys, Mahoney and Yang, 2023). Together, these findings suggest that reducing disparities is not simply about a capacity to pay, but related to the strategies people have to navigate their financial lives. Consistent with this, randomized financial-coaching interventions have shown measurable success, even in adulthood (Theodos, Stacy and Daniels, 2018; Modestino, Sederberg and Tuller, 2019). In contrast, large unconditional cash transfers do not affect delinquency once repayment patterns are established (Bartik et al., 2024), nor do restrictions on high-interest credit products (Bhutta, Goldin and Homonoff, 2016) and short-run financial relief (Dobbie and Song, 2020). Because these habits form early and are reinforced by parents and social networks, policies that cultivate sound credit practices during childhood and young adulthood appear to be promising policy pathways. More broadly, our patterns align with the conclusions of Edin, Shaefer and Nelson (2023) and others who suggest that segregation by race and class hinders economic mobility and perpetuates inequality across generations.

Our findings raise a deeper, unresolved question: why do some environments foster repayment norms while others do not? A growing historical and behavioral literature points to long-lasting "financial imprints" that could in principle generate the heterogeneity we document. Early-life macro shocks shape attitudes toward debt and risk well into adulthood (Malmendier and Nagel, 2011; Malmendier and Wachter, 2021). Further work shows that a range of traumatic episodes of financial exclusion—including the collapse of the Freedman's Savings Bank (Arthi, Richardson and Van Orden, 2024), the Tulsa massacre, and longer-term practices such as predatory retail credit markets and redlining in many urban areas (Hyman, 2011; Appel and Nickerson, 2016; Albright et al., 2021; Aaronson et al., 2023) have impacts that persist across generations.[67] These historical events can perhaps seed persistent gaps in financial literacy, trust in lenders, and repayment

[67] See also work documenting long run impacts of racial discrimination, lynching, and segregation (Andrews et al., 2017; Cook, Logan and Parman, 2018; Williams, Logan and Hardy, 2021; Baker, 2022)

behavior.[68] Our results show how, once such differences arise, they are transmitted forward across generations via childhood environments, magnifying the persistence of the initial shocks. We hope that the publicly available data we provide on repayment, credit scores, and balances (available on the Opportunity Atlas) can facilitate future explorations of these patterns. Pinpointing the precise channels—whether institutional, informational, or psychological—and identifying policies that can harness the potential power of credit markets to expand economic opportunity remains an important task for future research.

[68] They may also interact with place-specific credit access and limited resources in one's social networks. For example, a long literature has documented the disproportionate prevalence of alternative financial institutions in low-income and nonwhite neighborhoods (Faber, 2018, 2019; Graves, 2003; Small et al., 2021; Smith, Smith and Wackes, 2008)

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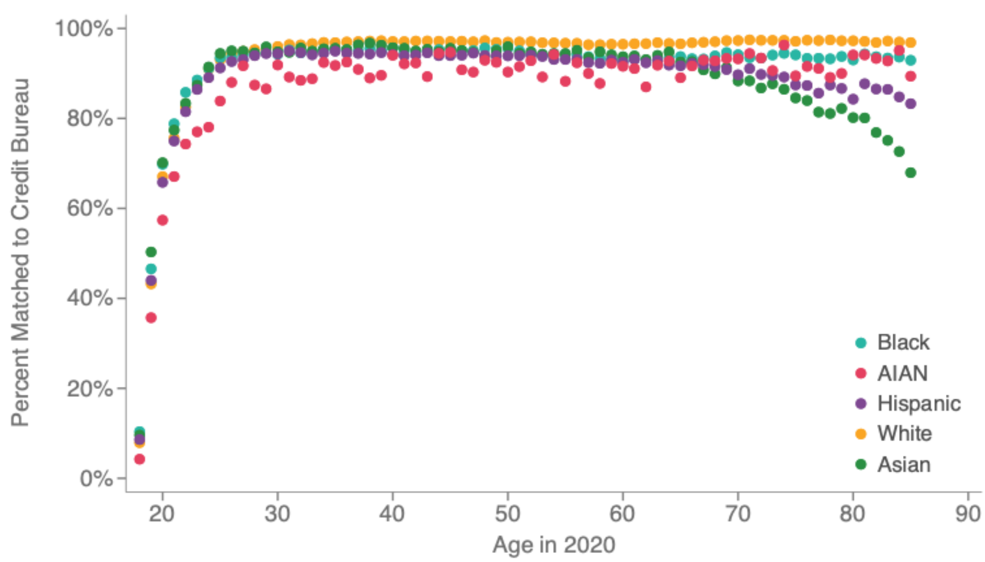
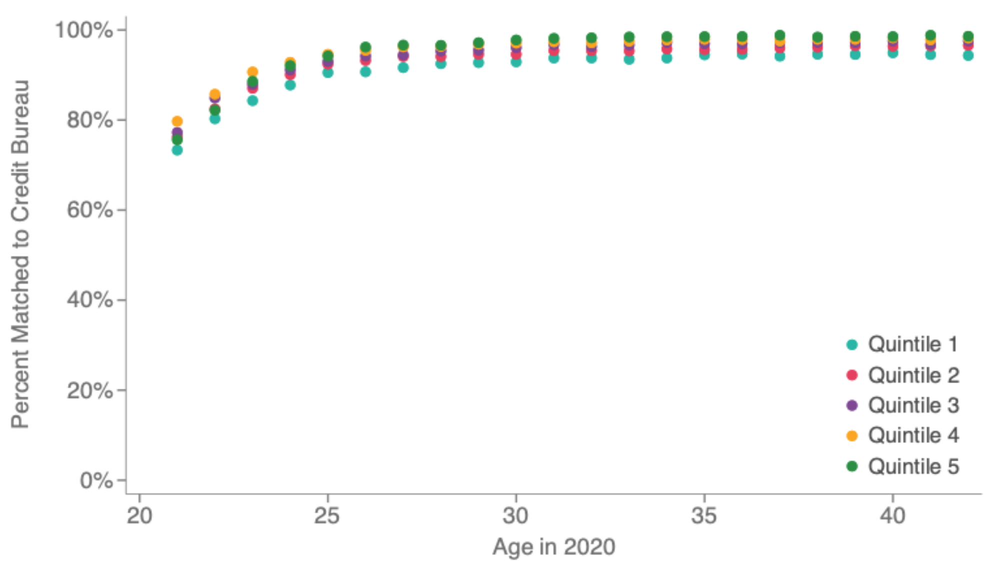
FIGURE I
Percent of Population with Credit File by Age

A. Race



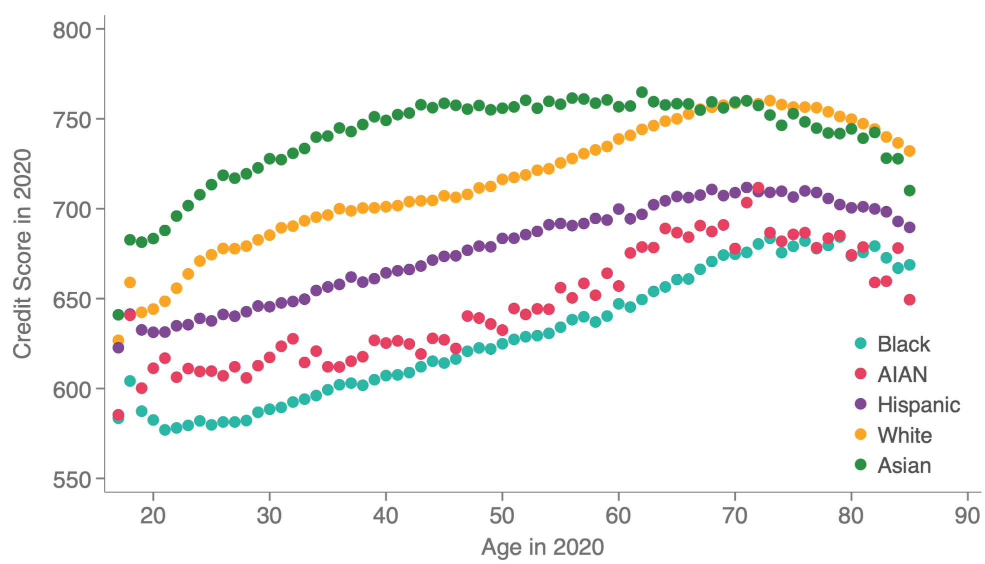
B. Parental Income Quintile



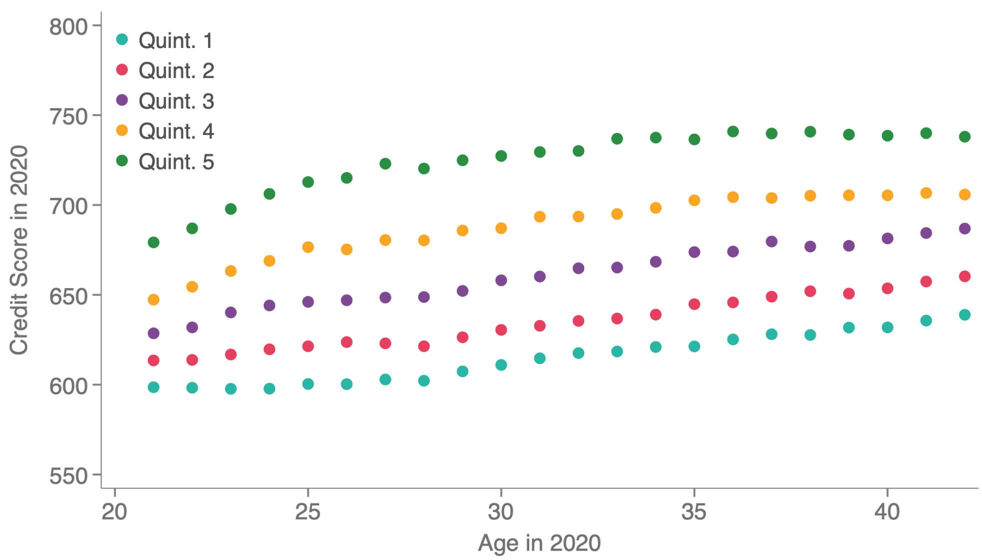
Notes: This figure presents the percentage of people in our population sample who have a credit file by age, race, and parental income in 2020. Panel A reports fractions by age and race. Panel B reports fractions by age and parental income quintile, restricting to the birth cohorts we are able to match to parents.

FIGURE II
Average Credit Scores by Age

A. Race

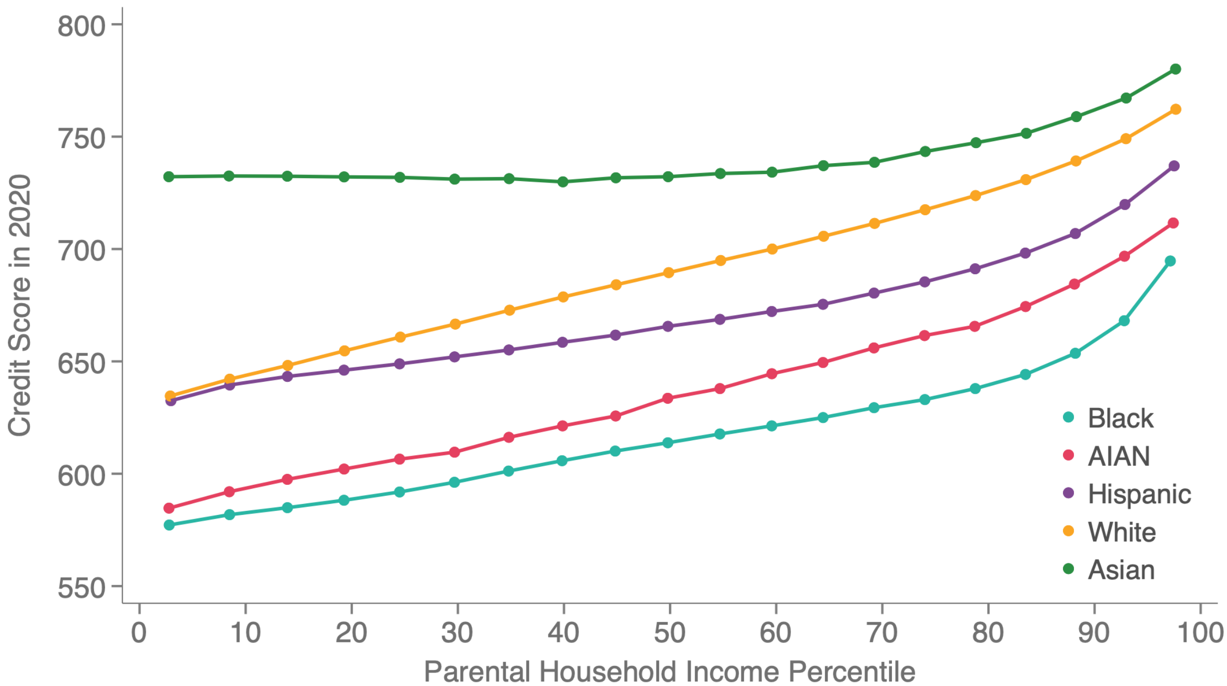


B. Parental Income Quintile



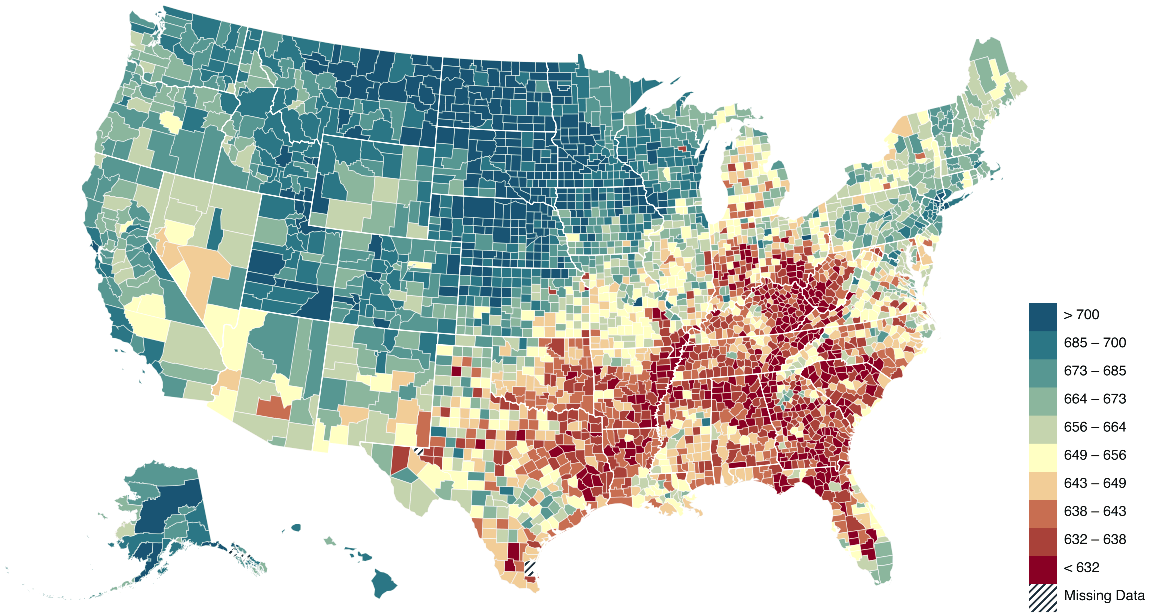
Notes: This figure presents the average credit scores in 2020 for our population sample by race and parental income. Panel A reports the average credit scores by age and race. Panel B reports the average credit scores by age and parental income, restricting to the birth cohorts we are able to match to parents. All averages are taken over the subset of individuals with credit scores.

FIGURE III
Credit Scores by Race and Parental Income



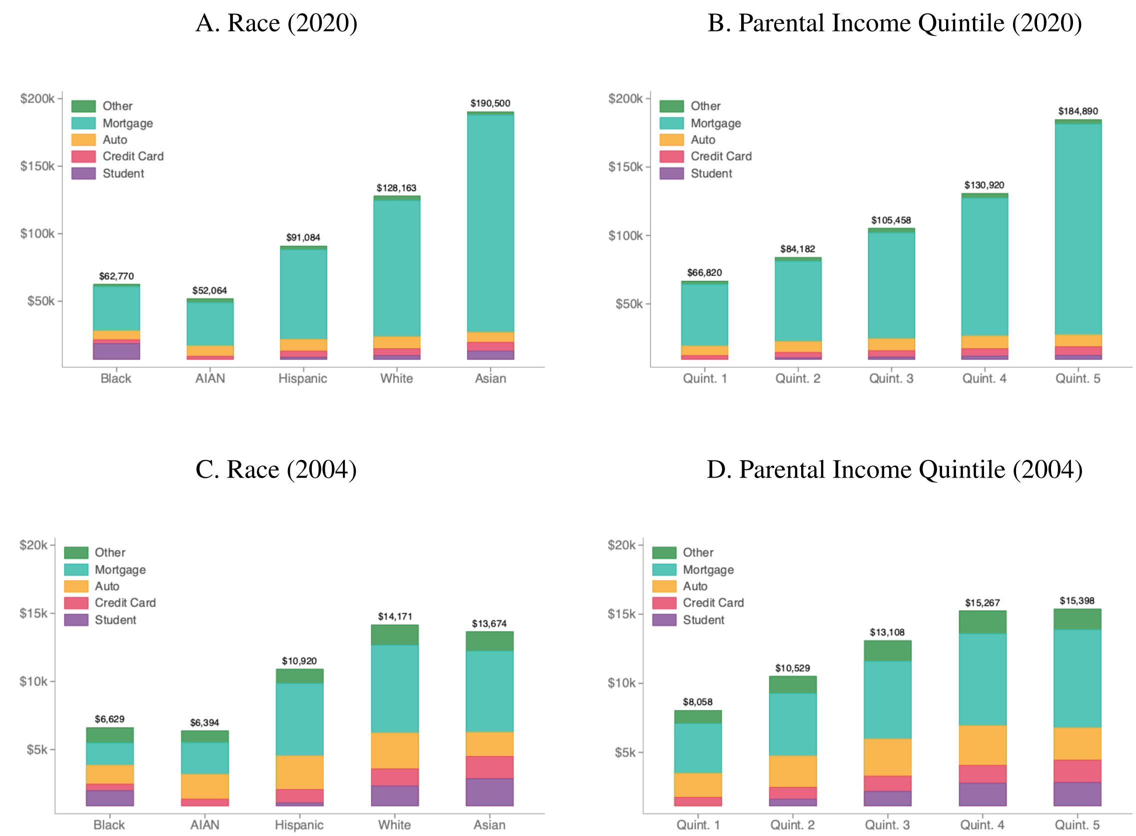
Notes: This figure presents the average credit scores in 2020 for our intergenerational sample (born between 1978 and 1985) by parental income percentile, separately by race. See Appendix Figure A.4 for a version of this figure that restricts the sample to those with U.S.-born mothers.

FIGURE IV
Geography of 2020 Credit Scores for White Individuals with 25th Percentile Parental Income



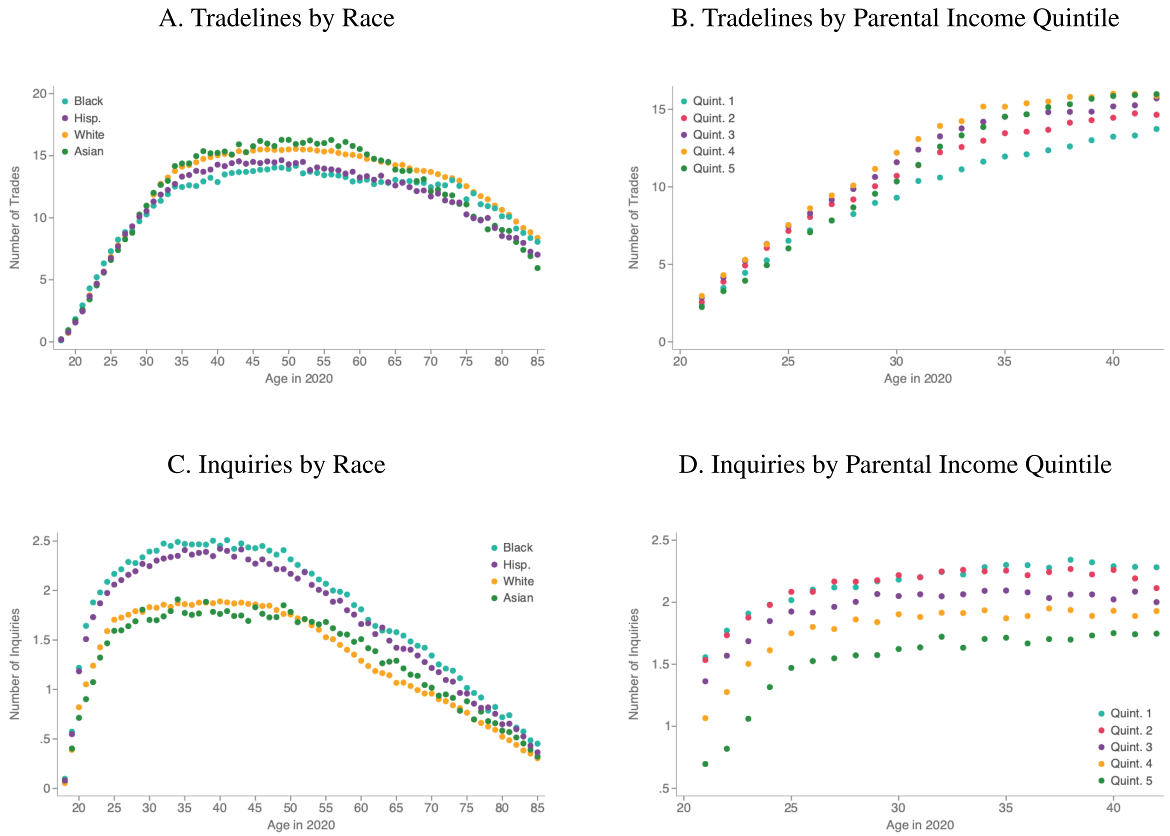
Notes: This map displays mean credit scores in 2020 for White individuals with parents at the 25th percentile of the national household income distribution in our intergenerational sample (born between 1978 and 1985) by the county in which they grew up. We first estimate the relationship between credit score and parental income rank using a lowess fit at the national level. For each county, we then regress individual credit scores on the transformed parental income rank (from the national lowess) to obtain the average credit score for individuals whose parents were at the 25th percentile nationally. Counties shown with black and white dashed lines are those with insufficient data.

FIGURE V
Composition of Total Debt



Notes: This figure presents a stacked bar chart of average debt holdings by type of credit in the intergenerational sample (born between 1978 and 1985) in 2004 and 2020. We present four credit types: mortgages, auto loans, credit card balances, and student loans, which comprise nearly all debt on credit reports. We also present a fifth "other" category. Panels A and C report average debt by race. Panels B and D report average debt by parental income quintile. Note that the vertical axis scale changes depending on the year of measurement, which is 2020 (Panels A and B) or 2004 (Panels C and D).

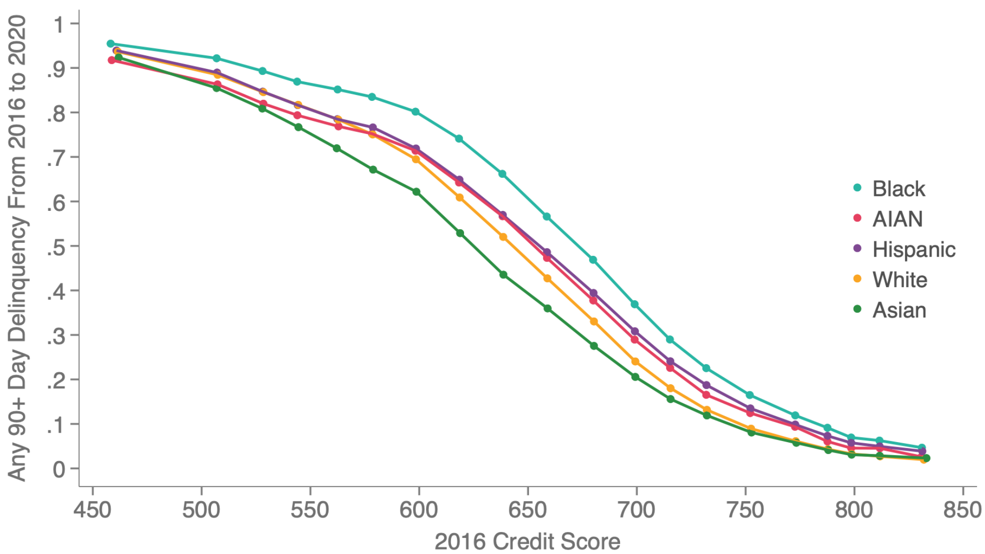
FIGURE VI
Number of Tradelines and Inquiries by Age



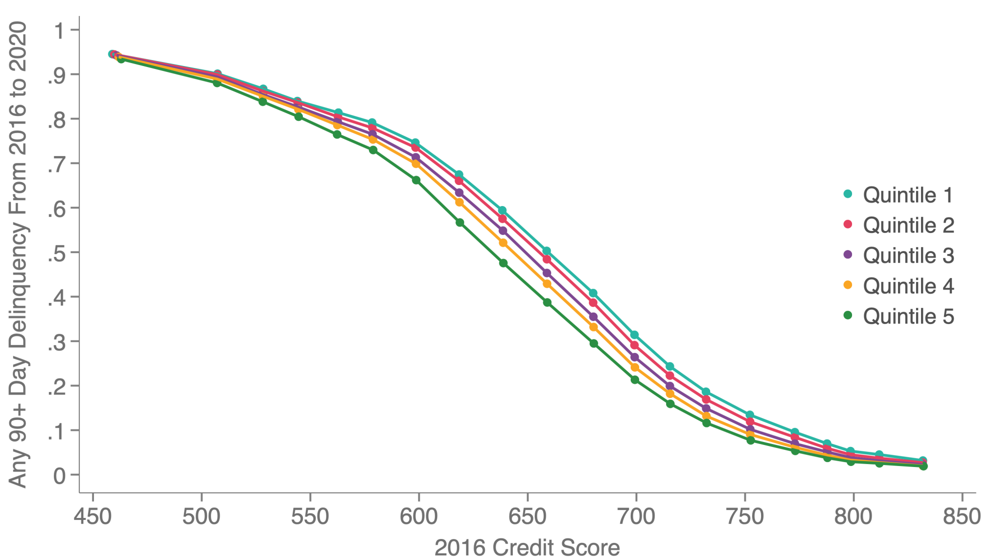
Notes: This figure presents the number of tradelines and inquiries by age in the population sample in 2020. Panel A presents tradelines by race. AIAN is omitted due to sample size. Panel B presents tradelines by parental income quintile, restricting to the birth cohorts we are able to match to parents. Tradelines include collections. We observe qualitatively similar patterns when omitting collections trades. Panel C presents inquiries by race. AIAN is omitted due to sample size. Panel D presents inquiries by parental income quintile, restricting to the birth cohorts we are able to match to parents.

FIGURE VII
Calibration Bias: Subsequent Non-Repayment Versus Credit Score

A. Race



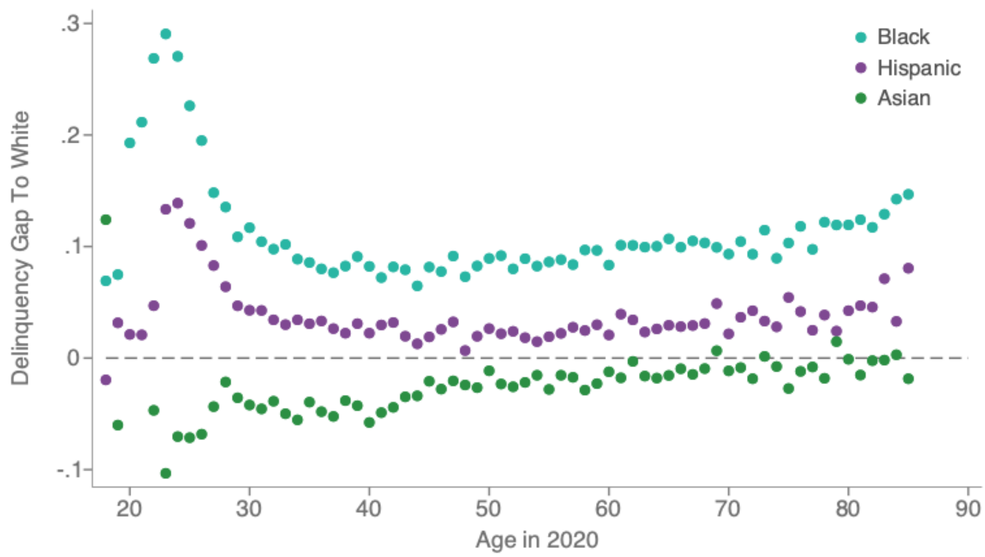
B. Parental Income Quintile



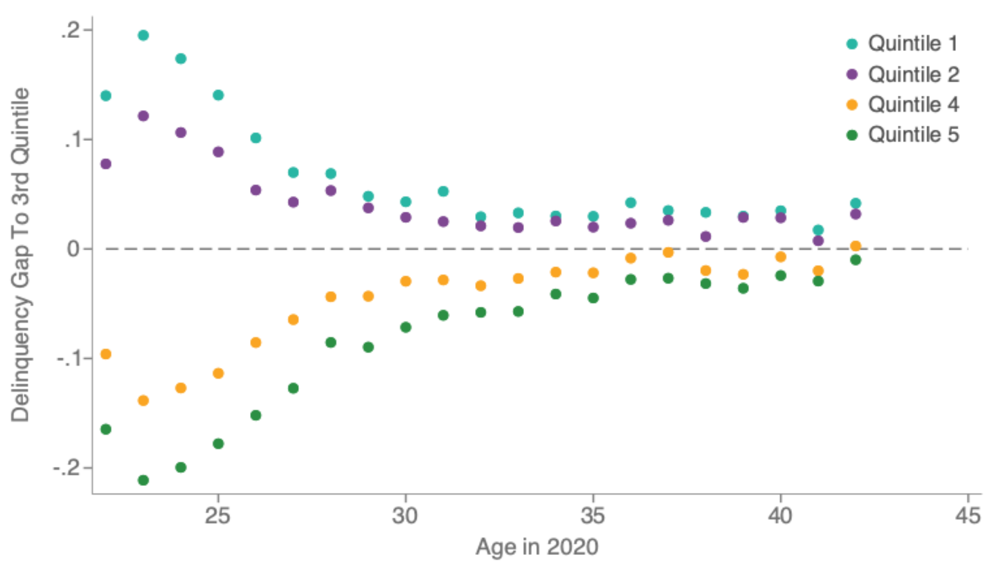
Notes: This figure presents the average 90+ day delinquency rate between 2016 and 2020 (using the 2020 credit file) as a function of the 2016 credit score on the horizontal axis, separately by group. Panel A reports separate series by race. Panel B reports separate series by parental income quintile. Both series use the intergenerational sample (born between 1978 and 1985).

FIGURE VIII
Calibration Bias by Age

A. Race (Relative to White)

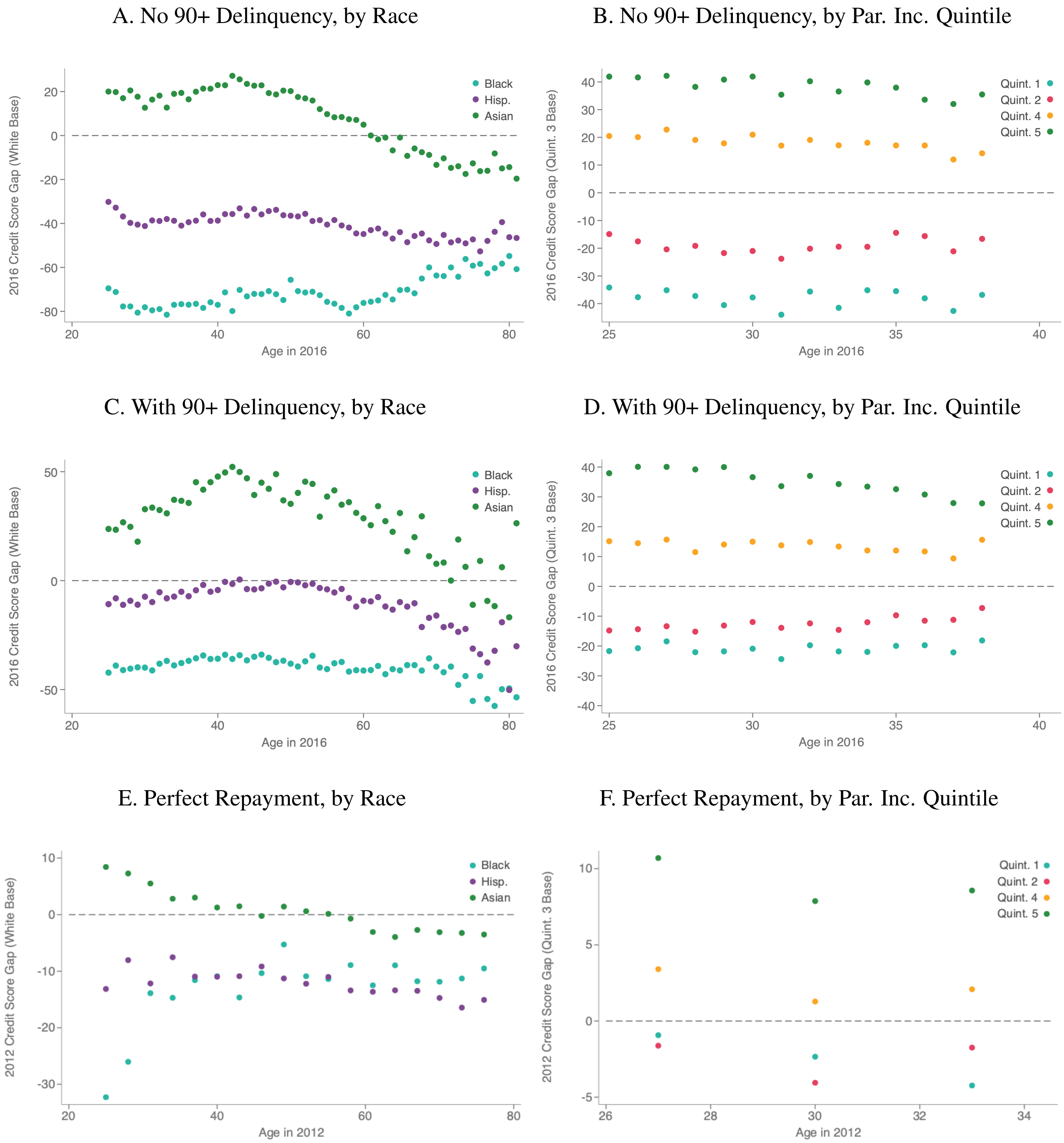


B. Parental Income Quintile (Relative to 3rd Quintile)



Notes: This figure presents estimated coefficients from separate OLS regressions of 90+ day delinquency between 2016 and 2020 against 2016 credit scores and race indicators (Panel A) or credit scores and parental income quintile indicators (Panel B) for our population sample. Panel A reports coefficients on indicators for race, where White is the omitted category. AIAN is omitted due to sample size. Panel B reports coefficients on indicators for parental income quintiles, where Quintile 3 is the omitted category, restricting to the birth cohorts we can match to parents.

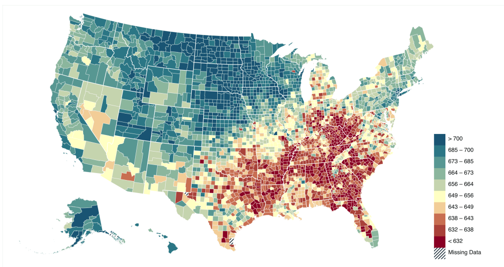
FIGURE IX
Balance Bias: Credit Score Gaps by Subsequent Repayment Status



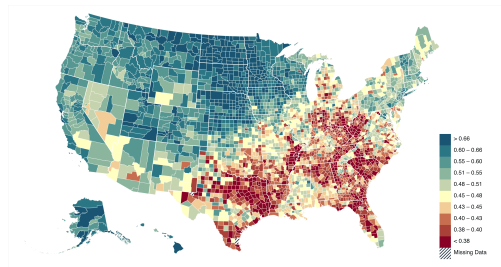
Notes: This figure presents a balance test for bias in credit scores by race and parental income quintile in the population sample. The left column (Panels A, C, and E) presents results by race, and the right column (Panels B, D, and F) does so by parental income quintile. In the first two rows, for each three-year age bin, we present the coefficients on race/parental income quintile indicators from a regression of the 2016 credit score on race/parental income quintile indicators, omitting White individuals/3rd quintile. Panels A and B restrict to the set of individuals who do not have a 90+ day delinquency during 2016-2020. Panels C and D restrict to the set of individuals who do have a 90+ day delinquency during 2016-2020. Panels E and F regress 2012 credit scores on race/parental income quintile indicators for the subset of individuals in our population sample who never made a payment over 30 days late at any point between 1997 and 2020. Panels B, D and F are restricted to the birth cohorts we can match to parents.

FIGURE X
Geography of 2020 Credit Scores for White Individuals with 25th Percentile Parental Income

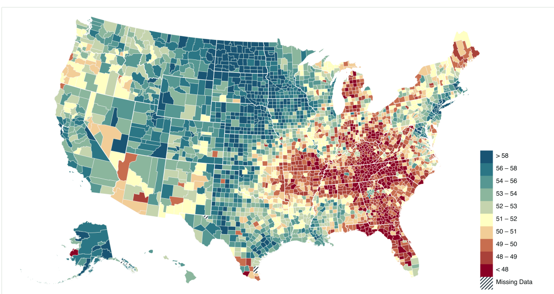
A. Credit Score



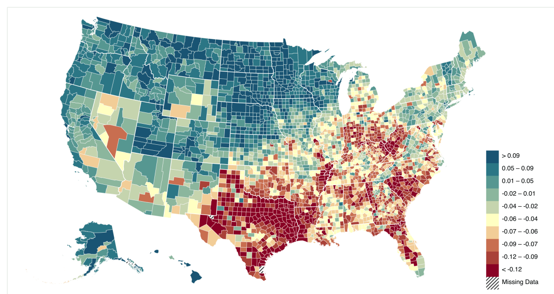
B. Repayment



C. Upward Mobility

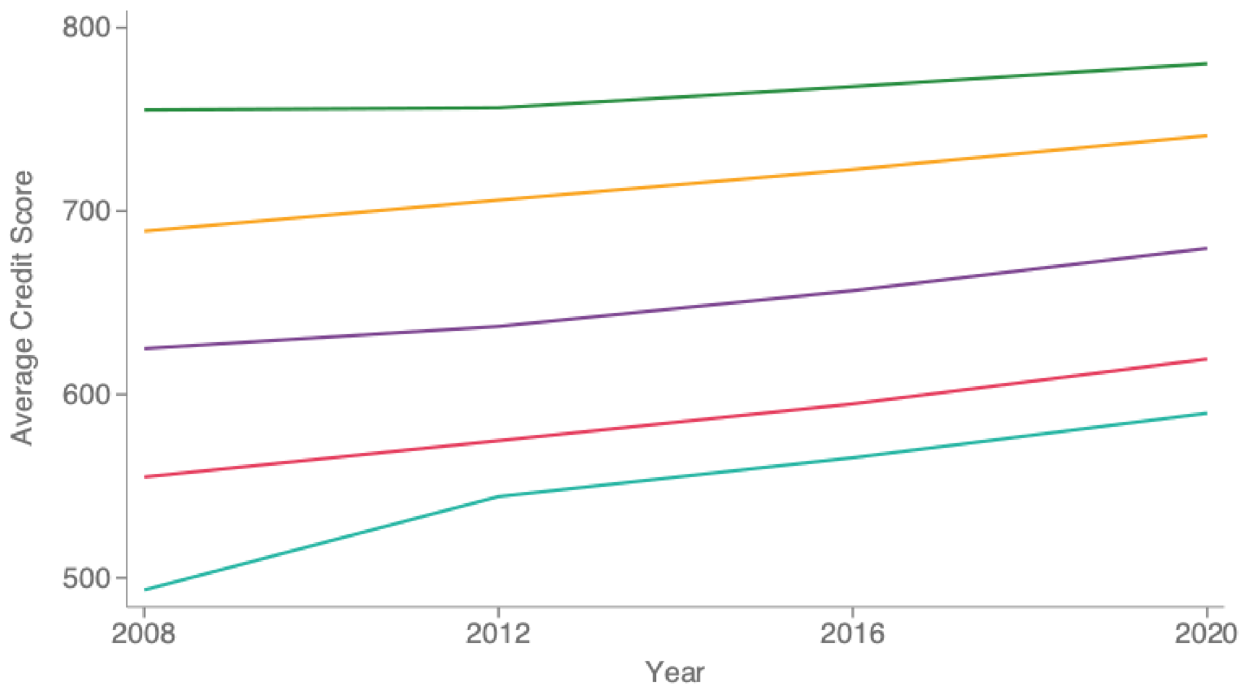


D. Residualized Repayment



Notes: This figure shows county-level estimates of credit scores (Panel A) and repayment (Panel B) in 2020 for White individuals growing up at the 25th percentile of parental income in the intergenerational sample (born between 1978 and 1985). Panel C presents estimates of county-level upward mobility, measured as child family income rank, from the Opportunity Atlas (Chetty et al., 2025). Panel D shows residualized repayment which we compute by taking the residuals of a regression of any 90+ delinquency from 2016 to 2020 on 2016 family income rank. We restrict the sample to individuals with positive family income in 2016.

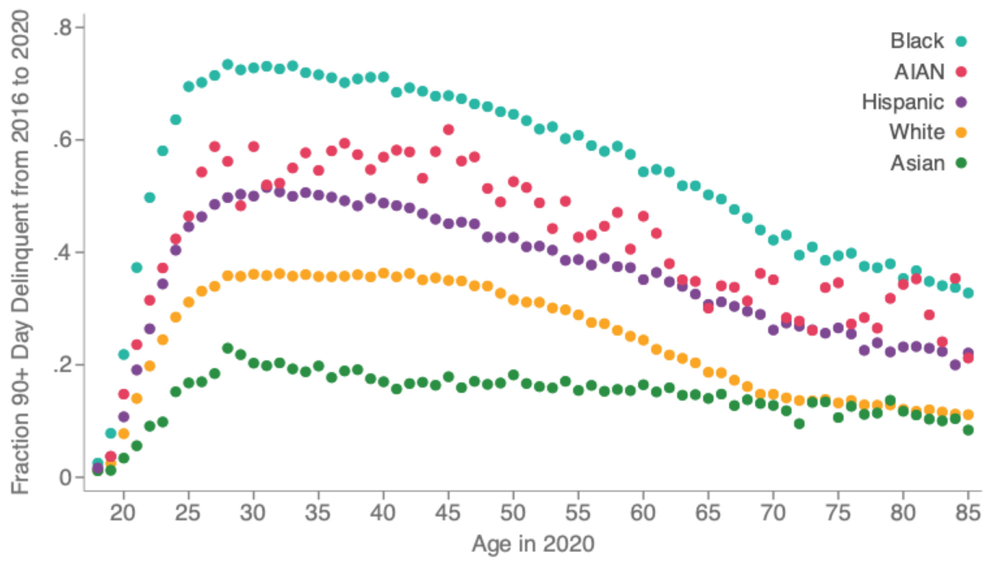
FIGURE XI
Credit Score Within-Person Persistence



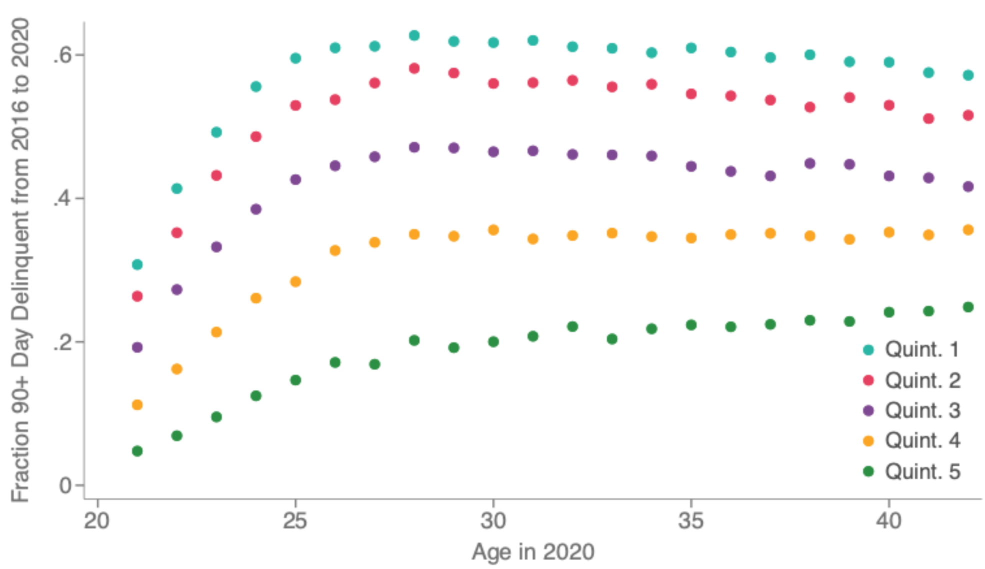
Notes: This figure bins people in the intergenerational sample (born between 1978 and 1985) into quintiles of their credit score in 2008. Holding this sample fixed using 2008 quintiles, it then plots the average credit scores of each of these groups in subsequent years.

FIGURE XII
90+ Day Delinquent Payments by Age

A. Race



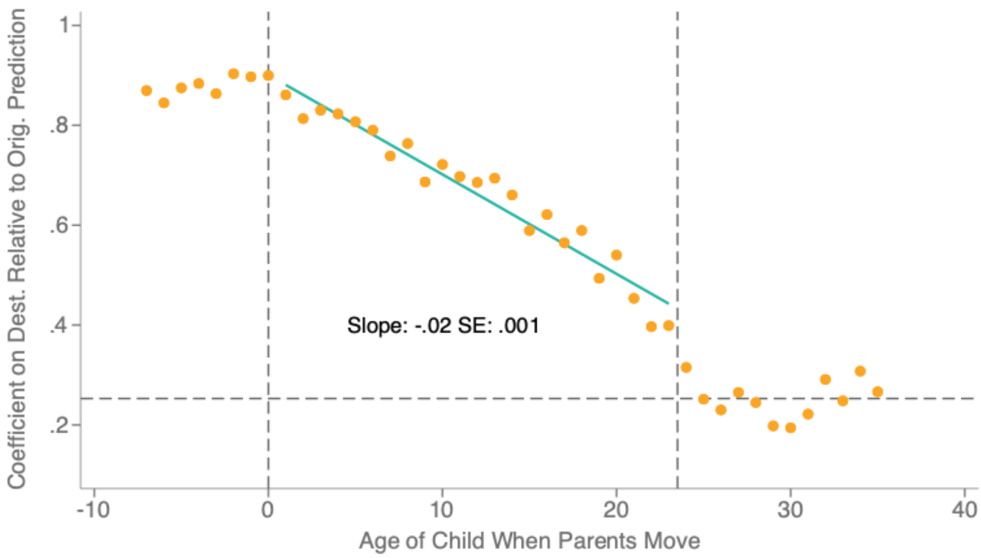
B. Parental Income Quintile



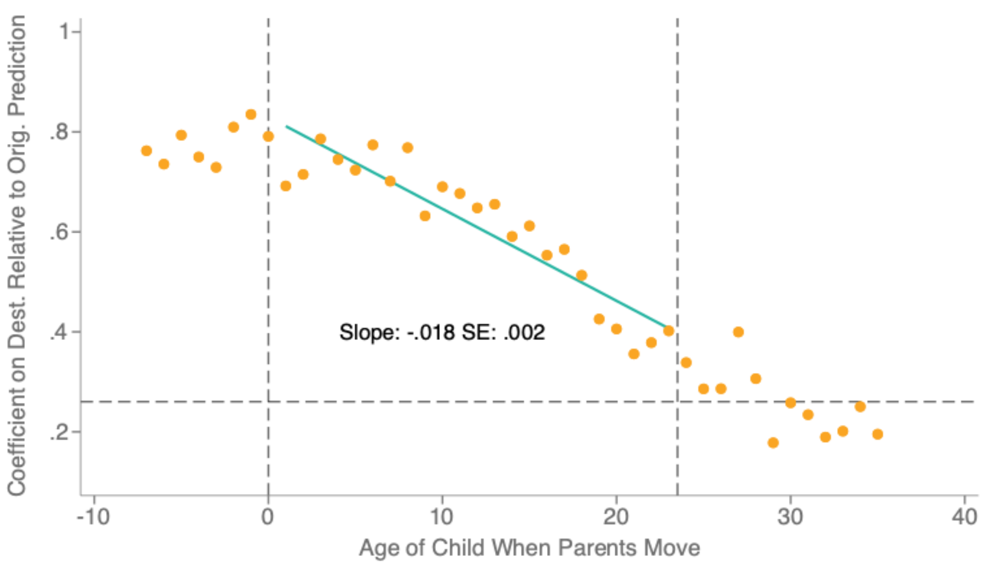
Notes: These figures shows the fraction of individuals with a late payment (90+ day late) between 2016 and 2020 by age in the population sample. Panel A reports fractions by age and race. Panel B reports fractions by age and parental income quintile, restricting to the birth cohorts we can match to parents.

FIGURE XIII
Childhood Exposure Effects for 90+ Day Delinquency

A. 90+ Delinquency



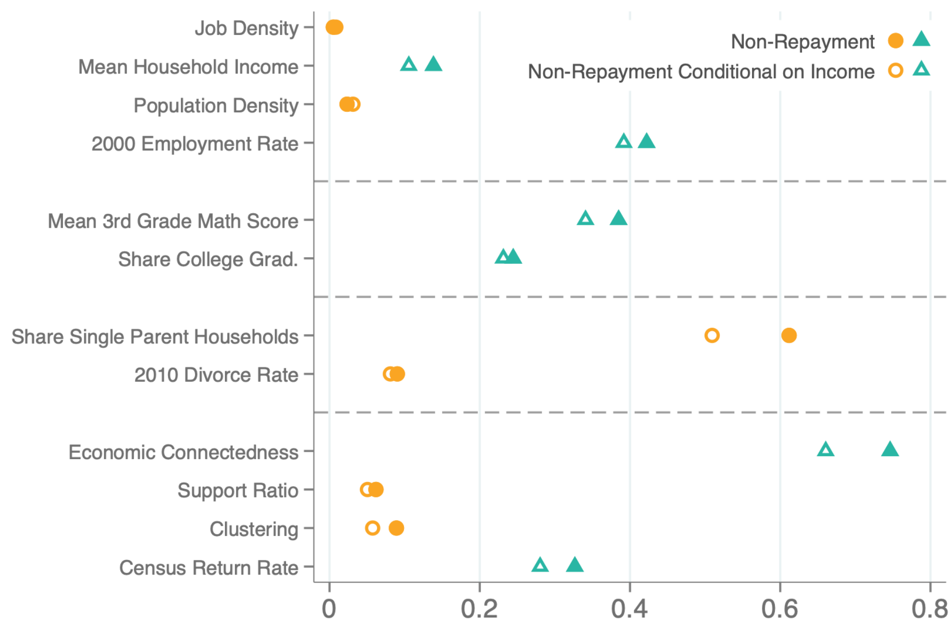
B. 90+ Day Delinquency with Family Fixed Effects



Notes: Panel A plots OLS estimates of the coefficients β_m versus the child's age when the parents move (m) using the specification in equation 3 in our intergenerational sample (born between 1978 and 1985). The outcome variable is an indicator for whether a child had a 90+ day delinquency between 2000 and 2004. We interpret the difference in coefficients, $\beta_{m-1} - \beta_m$, as the causal effect of spending age m of childhood in a place where outcomes of non one-time-movers are one percentile higher. The figure reports the slope of a regression of β_m on age, m, between ages 0 and 23, along with its standard error. Panel B does the same but includes family fixed effects in the specification.

FIGURE XIV
Correlates of Place Estimates

A. Non-Repayment



B. Household Income Rank

Notes: Each panel presents unweighted correlation coefficients between various county-level covariates and our county-level estimates at the 25th percentile of parental income (pooling across all racial groups). Each correlation coefficient is presented as an absolute value, with yellow circles denoting positive values and blue triangles denoting negative values. Panel A reports on the 90+ day delinquency rate and delinquency residualized on 2016 income rank. Panel B reports the correlation with upward income mobility, defined as the average household income rank of individuals who grew up in the county to parents at the 25th percentile of the income distribution, pooling across racial groups.

TABLE I
Mean and Median Credit Scores by Race/Parental Income in 2020

	(1)	(2)	(3)	(4)	(5)	(6)
	Intergenerational Sample			Population Sample		
	Mean	Median	Median w/Zeros	Mean	Median	Median w/Zeros
White	701	719	712	719	743	723
Black	601	581	571	621	604	583
Asian	741	781	776	746	779	762
Hispanic	659	655	644	670	671	643
AIAN	622	602	583	641	625	595
Quint. 1	630	611	596	615	594	574
Quint. 2	651	642	631	635	626	609
Quint. 3	679	685	676	661	664	649
Quint. 4	705	721	716	688	701	694
Quint. 5	740	775	772	725	744	736

Notes: This table presents mean and median credit scores in 2020 separately by race and parental income. Column 1 reports the mean credit score on the subset of the intergenerational sample (born between 1978 and 1985) that has a credit score. Column 2 reports the median credit score on the subset of the intergenerational sample that has a credit score. Column 3 reports the median score after imputing scores of zero for those with missing credit scores or files in the intergenerational sample. Column 4 reports the mean credit score on the subset of the population sample that has a credit score. Column 5 reports the median score among those who have a credit score in the population sample. Column 6 reports the median score after imputing scores of zero for those with missing credit scores or files in the population sample. The top panel reports means by race. The bottom panel reports means by parental income quintile. The bottom panel of Columns 4–6 restricts the population sample to the birth cohorts we can match to parents.

TABLE II
Mean Credit Scores by Race/Parental Income and Sex in 2020

	(1)	(2)	(3)	(4)
	Intergenerational Sample		Population Sample	
	Male	Female	Male	Female
White	703	700	719	719
Black	602	601	620	622
Asian	738	745	744	747
Hispanic	660	658	670	670
AIAN	625	619	644	639
Quint. 1	633	627	617	613
Quint. 2	654	649	636	634
Quint. 3	681	677	662	660
Quint. 4	706	703	689	688
Quint. 5	739	740	723	727

Notes: This table presents mean credit scores in 2020 separately by race, parental income, and sex. Columns 1 and 2 report mean credit scores for male and female individuals, respectively, in the intergenerational sample (born between 1978 and 1985). Columns 3 and 4 report mean credit scores for male and female individuals, respectively, in the population sample. The top panel reports means by race. The bottom panel reports means by parental income quintile. The bottom panel of Columns 3 and 4 restricts the population sample to the birth cohorts we can match to parents.

TABLE III
Highest and Lowest Average Credit Scores Among 100 Largest Counties

	County	State	Pooled	White P25	Asian P25	Black P25	AIAN P25	Hisp. P25	White P75
1	Bergen	NJ	724	707	752	621	638	674	741
2	DuPage	IL	723	696	748	604	675	668	735
3	Norfolk	MA	721	688	765	636	623	668	732
4	Fairfax	VA	721	696	748	624	651	680	739
5	Nassau	NY	718	711	751	618	634	670	743
6	San Francisco	CA	718	712	758	606	632	671	742
7	Montgomery	PA	716	688	756	602	617	648	735
8	Middlesex	MA	715	684	727	637	637	653	731
9	Hennepin	MN	713	694	708	605	594	655	739
10	Montgomery	MD	713	695	754	627	634	675	740
91	Philadelphia	PA	653	666	734	594	596	627	718
92	Fulton	GA	653	672	737	591	617	651	725
93	Duval	FL	653	640	699	590	610	642	698
94	Prince George's	MD	652	659	730	606	618	660	716
95	Bronx	NY	650	687	730	618	625	642	728
96	DeKalb	GA	650	674	735	597	621	656	725
97	Jefferson	AL	647	640	733	584	596	622	705
98	Shelby	TN	645	652	726	584	605	638	709
99	Hidalgo	TX	644	648	714	622	627	634	707
100	Baltimore city	MD	627	640	709	589	599	624	710

Notes: This table ranks the ten highest- and ten lowest-scoring counties among the 100 most-populous U.S. counties on the basis of the 2020 VantageScore 4.0 credit score for individuals in our intergenerational sample (born between 1978 and 1985). The "Pooled" column reports each county's overall mean score, calculated as the weighted average of credit score means for residents from the 25th and 75th parental-income percentiles across all race groups. The remaining columns present race-specific means for individuals whose parents were at the 25th percentile of the national income distribution (White, Asian, Black, AIAN, and Hispanic) and, for comparison, for White individuals from the 75th percentile. Values are simple county averages with no additional controls.

TABLE IV
Alternative Credit Usage by Race (Survey of Consumer Finances)

	(1)	(2)	(3)	(4)
	Payday Loan	Payday Loan	Payday Loan	Payday Loan
Black	0.045***	0.057***	0.043***	0.056***
	(0.005)	(0.017)	(0.005)	(0.017)
Asian	0.013***	0.001	0.011**	0.001
	(0.004)	(0.011)	(0.004)	(0.011)
Hispanic	–0.020***	–0.030***	–0.018***	–0.030***
	(0.003)	(0.006)	(0.003)	(0.006)
Log HH Income			–0.004***	–0.001
			(0.001)	(0.002)
Age 22–30		X		X
White Mean	0.023	0.030		
N	21,645	1,901	21,645	1,901
R^2	0.009	0.013	0.010	0.013

Notes: This table reports estimated coefficients from OLS regressions of payday loan usage on race indicators using data from the SCF. Each column reports coefficients from a weighted linear-probability model in which the dependent variable equals 1 if the SCF respondent reports having taken out a payday loan in the past 12 months (variable x7063). We pool the 2013, 2016, 2019, and 2022 SCF cross-sections and keep observations with non-missing values of the dependent variable. The omitted race category is non-Hispanic White. Columns 1 and 3 use the full adult sample (ages 18+), while Columns 2 and 4 restrict the sample to respondents ages 22–30. Columns 3 and 4 additionally control for log household income. All regressions are weighted by the SCF household sampling weight x42001 (implicate 1). Standard errors (in parentheses) are conventional weighted-OLS standard errors. Statistical significance is denoted *** p < 0.01, ** p < 0.05, * p < 0.10.

TABLE V
Relationship Between 90+ Day Delinquency and Race/Class (2008)

Panel A: No Credit Score Control							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	0.272***	0.249***	0.186***	0.187***	0.193***	0.235***	0.218***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.004)	(0.004)
Asian	-0.161***	-0.173***	-0.113***	-0.108***	-0.033	-0.019***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.035)	(0.004)	(0.004)
Hispanic	0.114***	0.111***	0.091***	0.090***	0.098***	0.121***	0.092***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.002)	(0.003)
Parent Inc.	-0.458***	-0.446***	-0.275***	-0.272***	-0.150***	-0.147***	-0.119***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.003)	(0.003)
N	215,300	215,300	215,300	215,300	78	2,970	2,210
R^2	0.140	0.150	0.240	0.242	0.276	0.114	0.259
Panel B: With Credit Score Control							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	0.134***	0.130***	0.107***	0.108***	0.115***	0.124***	0.115***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.003)	(0.004)
Asian	-0.065***	-0.068***	-0.042***	-0.039***	0.008	0.008**	0.007*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.030)	(0.004)	(0.004)
Hispanic	0.069***	0.069***	0.062***	0.061***	0.066***	0.071***	0.055***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)	(0.002)	(0.003)
Parent Inc.	-0.195***	-0.195***	-0.118***	-0.116***	-0.060***	-0.048***	-0.039***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.022)	(0.003)	(0.003)
N	215,300	215,300	215,300	215,300	78	2,970	2,210
R^2	0.345	0.345	0.379	0.380	0.401	0.288	0.391
Inc. 2004		X	X	X	X	X	X
Inc. Vec.			X	X	X	X	X
Def. Comp.				X	X	X	X
Home Equity				X	X	X	X
Liquid Assets					X		
Net Wealth					X		
Employer FE							X
Sample	All	All	All	All	SIPP	Stable	Stable

Notes: This table reports results from OLS regressions of 90+ day delinquency between 2004 and 2008 on race and parental income rank, with and without controlling for credit score, across different samples and model specifications. All specifications use our intergenerational sample. Panel A presents estimates without credit score as a covariate; Panel B includes 2004 credit score as an additional control. Each column cumulatively adds the controls listed at the bottom of the table. The unit of observation is the individual. Coefficients are reported with standard errors in parentheses. Sample restrictions are defined in the last row: "SIPP" refers to individuals matched to the SIPP sample; "Stable" refers to individuals whose household income rank remains within ten percent of their 2004 rank every year until 2009, who remain with the same employer from 2005 to 2009 and have one W-2 from 2005 to 2009. We only have W-2's going back to 2005, which is why we are unable to make all of the restrictions going back to 2004. Column 7 adds an additional sample restriction of stable marital status from 2004 to 2009. Statistical significance is denoted *** p < 0.01, ** p < 0.05, * p < 0.10. N is reported in 100s.

TABLE VI
Parent Credit Score Predicts Child Delinquency (2008)

	(1)	(2)	(3)	(4)	(5)	(6)
	90+ Day Delinquency					
Par. Credit Score Rank	-0.751***	-0.732***	-0.577***	-0.544***	-0.507***	-0.444***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.112)
Income Rank in 2004		-0.148***	-0.138***	-0.102***	-0.127***	0.043
		(0.001)	(0.001)	(0.001)	(0.002)	(0.079)
Parent Income Rank			-0.270***	-0.237***	-0.162***	-0.103
			(0.001)	(0.001)	(0.002)	(0.108)
Child Wealth				X	X	X
Par. Education					X	X
Par. Wealth						X
N	4,156,000	4,156,000	4,156,000	4,156,000	1,052,000	600
R^2	0.135	0.142	0.159	0.179	0.174	0.181

Notes: This table presents estimated coefficients from an OLS regression of any 90+ day delinquency from 2004 to 2008 against parental credit score rank in 2004. Column 1 reports a univariate regression of delinquency on parental credit score rank. The next columns add controls. Column 2 adds the child's household income rank in 2004. Column 3 adds the child's parental income rank. Column 4 adds our proxy measure of wealth, which is the sum of deferred compensation from 2005 to 2016 and housing wealth. Column 5 adds parental education fixed effects. Column 6 adds parent liquid and net wealth from the SIPP in 2003 and 2004. Statistical significance is denoted *** p < 0.01, ** p < 0.05, * p < 0.10.

TABLE VII
Causal Effect of Annual Year of Exposure to Hometowns

	(1)	(2)	(3)	(4)
	Pooled Race Δ		By Race Δ	
Age Spline Component	Base	Fam. FE	Base	Own vs. Other
Age 0 to 23 (Childhood)	-0.019***	-0.015***	-0.022***	-0.024***
	(0.001)	(0.003)	(0.001)	(0.003)
Age -7 to 0 (Pre-Birth)	0.007**	0.009	-0.007	-0.036**
	(0.004)	(0.009)	(0.005)	(0.016)
Age 23 to 35 (Adulthood)	0.001	-0.015*	0.011***	-0.003
	(0.002)	(0.008)	(0.003)	(0.009)
Age 0 to 23 (Other)				0.002
				(0.003)
Age -7 to 0 (Other)				0.030*
				(0.017)
Age 23 to 35 (Other)				0.011
				(0.008)

Notes: This table presents estimates from the parametric movers design regression, which models outcome slopes as a three-piece linear spline by age at move: pre-birth (Age −7 to 0), childhood (Age 0 to 23), and adulthood (Age 23 to 35). "Pooled Race Δ" columns show the coefficient where "move quality" is pooled over race. "Fam. FE" adds family fixed effects. Siblings are defined as individuals who have the same claiming parents. "By Race Δ" columns show specification where we allow the "move quality" to differ by race. "Own vs. Other Race" restricts to Black and White individuals and includes controls for the "move quality" of your own race and the other race. Statistical significance is denoted *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE VIII
Financial Literacy and Non Repayment (SCF)

	(1)	(2)	(3)	(4)	(5)
Financial Literacy: Inflation	–0.108***	–0.087***	–0.078***		–0.081***
	(0.029)	(0.029)	(0.028)		(0.028)
Financial Literacy: Diversification	–0.039	–0.030	–0.017		–0.021
	(0.029)	(0.028)	(0.029)		(0.027)
Financial Literacy: Interest	0.015	0.026	0.017		0.014
	(0.029)	(0.028)	(0.028)		(0.028)
Log HH Income		–0.085***	–0.053***	–0.082***	–0.071***
		(0.015)	(0.018)	(0.014)	(0.015)
Log Net Wealth			–0.037***		
			(0.010)		
Black				0.185***	0.177***
				(0.034)	(0.034)
Hispanic				0.035	0.033
				(0.034)	(0.034)
Asian				0.178	0.212
				(0.196)	(0.196)
N	1,495	1,495	1,495	1,495	1,495
R^2	0.021	0.049	0.066	0.065	0.074
Financial Literacy Joint F-Test (P-val)	0.000	0.002	0.008		0.004

Notes: This table reports OLS regression estimates of how financial literacy and race relate to the likelihood that a SCF respondent missed any loan or bill payment in the past 12 months. We pool the 2013, 2016, 2019, and 2022 SCF cross-sections, restrict the sample to respondents aged 22–30 with non-missing values of the dependent variable, and weight all regressions by the SCF household sampling weight x42001 (implicate 1), leaving 1,495 observations. Financial literacy is captured by indicators for correctly answering each of the three "Big 3" financial literacy questions: inflation, diversification, and compound interest. "Financial Literacy Inflation" asks "Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?" "Financial Literacy Savings" asks "Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?" "Financial Literacy Stocks" asks "Do you think that the following statement is true or false? 'Buying a single company stock usually provides a safer return than a stock mutual fund."' Column 1 includes only these financial literacy indicators. Column 2 adds log household income along with a dummy for missing log income; Column 3 further includes log net wealth and its missing-value dummy. Column 4 drops the literacy variables and instead introduces dummies for Black, Hispanic, and Asian respondents (non-Hispanic White omitted) while retaining the income controls. Column 5 combines the literacy indicators and race dummies with the income controls. The bottom row reports the p-value from a joint F-test that the coefficients on the three literacy indicators are simultaneously zero in the columns where they appear. Standard errors, shown in parentheses, are conventional weighted-OLS standard errors. Statistical significance is denoted *** p < 0.01, ** p < 0.05, * p < 0.10.

TABLE IX
Informal Transfers Incidence by Group (Prolific Survey)

	(1)	(2)	(3)	(4)
	Gave Fncl Assist (1,000s)	Gave Fncl Assist (Freq)	Times Asked for Help	Amount Could Borrow (1,000s)
Black	0.154	0.811***	1.671***	–0.443***
	(0.112)	(0.145)	(0.257)	(0.161)
Parent Education	0.051**	0.081***	0.111**	0.183***
	(0.020)	(0.026)	(0.045)	(0.028)
Chldhd Cnty Repayment Rate	–1.410**	–3.588***	–5.334***	0.766
	(0.617)	(0.798)	(1.414)	(0.884)
N	702	702	702	702
R^2	0.022	0.102	0.103	0.066

Notes: This table reports OLS estimates from our Prolific survey of 702 U.S. adults aged 22–30 that relate three demographic factors to the incidence of informal financial transfers. Columns 1–4 use, respectively, the (i) annual dollar amount given to family or friends (in \$1,000s), (ii) frequency of giving such assistance, (iii) number of times the respondent was asked for financial help over the past three years, and (iv) dollar amount the respondent believes they could borrow from family or friends (in \$1,000s) as dependent variables. Every specification includes an indicator for Black respondents, a continuous measure of parental education (11 years = less than high school, 12 = high school graduate, 14 = technical/community college, 16 = college graduate, 18 = master's degree, 20 = professional or doctoral degree), and the average debt-repayment rate in the respondent's childhood county. All regressions are unweighted, and conventional OLS standard errors are shown in parentheses. Statistical significance is denoted *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE X
Informal Transfers and Non Repayment (Prolific Survey)

	(1)	(2)	(3)	(4)	(5)
Black	0.111***	0.068*	0.037	0.046	0.020
	(0.040)	(0.040)	(0.039)	(0.039)	(0.039)
Parent Education	–0.014*	–0.016**	–0.016**	–0.009	–0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Chldhd Cnty Repayment Rate	–0.449**	–0.265	–0.211	–0.208	–0.165
	(0.218)	(0.217)	(0.213)	(0.213)	(0.210)
Give Financial Assistance ($1,000s)		–0.006	–0.008	0.017	0.013
		(0.015)	(0.014)	(0.015)	(0.015)
Give Financial Assistance (Freq)		0.057***	0.016	0.052***	0.016
		(0.011)	(0.013)	(0.011)	(0.013)
Times Asked for Help			0.038***		0.035***
			(0.007)		(0.007)
Amount Could Borrow ($1,000s)				–0.048***	–0.043***
				(0.009)	(0.009)
Education Controls	X	X	X	X	X
Dependent Variable Mean	0.526	0.526	0.526	0.526	0.526
N	702	702	702	702	702
R^2	0.027	0.065	0.103	0.098	0.129

Notes: This table reports OLS regression estimates from regressions where the dependent variable equals 1 if the respondent missed any loan or bill payment in the past 12 months. The sample consists of 702 U.S. Prolific participants aged 22–30 with non-missing responses. Every specification includes a Black indicator, a continuous measure of parental education (11 years = less than high school, 12 = high school graduate, 14 = technical/community college, 16 = college graduate, 18 = master's degree, 20 = professional or doctoral degree), the average debt-repayment rate in the respondent's childhood county, and controls for the respondent's own educational attainment (coded identically to parental education). Column 1 contains only these baseline covariates; Column 2 additionally controls for the annual dollar amount (in $1,000s) and frequency with which the respondent gives financial assistance to family or friends; Column 3 further adds the number of times the respondent was asked for financial help in the past three years; Column 4 instead adds the amount (in $1,000s) the respondent could borrow from family or friends; Column 5 includes the full set of financial network controls. In unreported specifications we include controls for income as well but the results are qualitatively similar. All estimates use conventional (non-robust) standard errors, shown in parentheses. Statistical significance is denoted *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Table IX reports the incidence of the four types of informal transfers by race, parental income, and childhood county repayment level.

TABLE XI
Alternative Credit Use by Race, Parental Income, and Geography (Prolific Survey)

Panel A: Usage

	(1)	(2)	(3)	(4)	(5)	(6)
	Payday Loan	Payday App	Auto Title	Pawn Shop	BNPL	Rent-to-Own
Black	0.094***	0.113***	0.058**	0.023	0.118***	0.043
	(0.034)	(0.034)	(0.025)	(0.022)	(0.039)	(0.027)
Parent Education	0.005	–0.007	–0.006	0.005	–0.019**	–0.004
	(0.006)	(0.006)	(0.005)	(0.004)	(0.007)	(0.005)
Chldhd Cnty Delinquency Rate	0.302	0.097	–0.146	0.296**	0.402*	0.236
	(0.186)	(0.185)	(0.137)	(0.124)	(0.214)	(0.148)
N	702	702	702	702	702	702
R^2	0.048	0.024	0.017	0.015	0.039	0.015
Education	X	X	X	X	X	X

Panel B: Repayment

	(1)	(2)
	Missed Payment	Missed Payment
Black	0.111***	0.046
	(0.040)	(0.038)
Parent Education	–0.014*	–0.011
	(0.007)	(0.007)
Chldhd Cnty Delinquency Rate	0.449**	0.244
	(0.218)	(0.205)
N	702	702
R^2	0.027	0.161
Education	X	X
Alt Financial Svcs		X

Notes: This table reports OLS regression estimates from our Prolific survey of 702 U.S. adults aged 22–30. Panel A reports six separate linear-probability models in which the dependent variable is an indicator for having used, in the past year, each of the following alternative financial services: (i) payday loan, (ii) a wage-advance "payday" app, (iii) an auto title loan, (iv) a pawn shop loan, (v) buy-now-pay-later financing (BNPL), and (vi) rent-to-own credit. Each specification includes three explanatory variables—the childhood county debt delinquency rate, an indicator for Black respondents, and the respondent's highest-educated parent's education level—along with a control for the respondent's own education. Education is coded as a continuous measure of parental education (11 years = less than high school, 12 = high school graduate, 14 = technical/community college, 16 = college graduate, 18 = master's degree, 20 = professional or doctoral degree). Panel B studies repayment outcomes: Column 1 regresses a missed payment indicator on the same three explanatory variables (plus education dummies); Column 2 adds the six alternative financial services indicators from Panel A to assess whether differences in product use account for racial, socioeconomic, or geographic gaps in repayment. All regressions are unweighted; standard errors in parentheses are conventional OLS standard errors. Statistical significance is denoted *** p < 0.01, ** p < 0.05, * p < 0.10.

A Data Appendix

A.A Linking Credit Bureau Data to Census Data

We link the major credit bureau data to the administrative data housed at the Census Bureau as follows. For the intergenerational sample, the 1978-1985 birth cohorts, the credit bureau identifies all individuals in their data who were born during those years and securely transfers the data, including a hashed version of the SSN, to the Census Bureau. Census and the credit bureau agreed upon a hashing algorithm that is not known to researchers or anyone interacting with the data at Census, allowing us to perform this match while ensuring confidentiality. The Census Bureau replaces the hashed SSNs from the credit bureau data with anonymized Protected Identification Keys (PIK) that facilitate linkages with other data housed at the Census Bureau, including the Decennial censuses, ACS, and federal income tax returns. We then merge the credit bureau data to the Census and tax records for all individuals in the 1978-1985 birth cohorts using the PIK. The process is analogous for the population sample, as well as the 10% sample of the 1935-1970 birth cohorts, who roughly correspond to the parents of the intergenerational sample. For the population sample, the credit bureau identifies all individuals who were alive as of 2004 and selects a 1% subset based on a sequence of digits in the individuals' SSNs that was not known to researchers. Similarly, for the 10% sample of the 1935-1970 cohorts, the credit bureau identifies all members of those birth cohorts and selects a 10% sample based on a sequence of digits in the individuals' SSNs that was not known to researchers. Because we observe our full target populations in the Census and tax data, we are therefore able to identify individuals who do not appear in the credit bureau data due to missing credit histories, thereby including so-called "credit invisibles" in our study, though we caution that our target population excludes the subset of the population who has not been assigned a PIK.

A.B The Survey of Income and Program Participation (SIPP)

The SIPP is a nationally representative longitudinal survey that focuses on program participation and includes questions on assets and liabilities. Since 1996, this survey has followed respondents for about four years, and each new panel is begun near the end of the previous one, albeit with some interruptions. For this paper, we use the 2001, 2004, 2014, and 2018 panels.[69] Participants are interviewed every four months, with each interview containing different, repeated questions in various topical modules. Generally speaking, participants were asked about assets and liabilities, once per year. In earlier panels, these questions were asked at the household level, while in later panels, these questions were asked of individuals. For continuity, we sum these asset and liability values to create household measures even in later years. There have been slight changes to the wealth questions over time. All panels that we use include questions about home equity, vehicle equity, business equity, interest earning assets at banking institutions, interest earning assets

[69]Beginning in 2018, the design switched to overlapping panels, where approximately one-quarter of participants cycle in and out each year

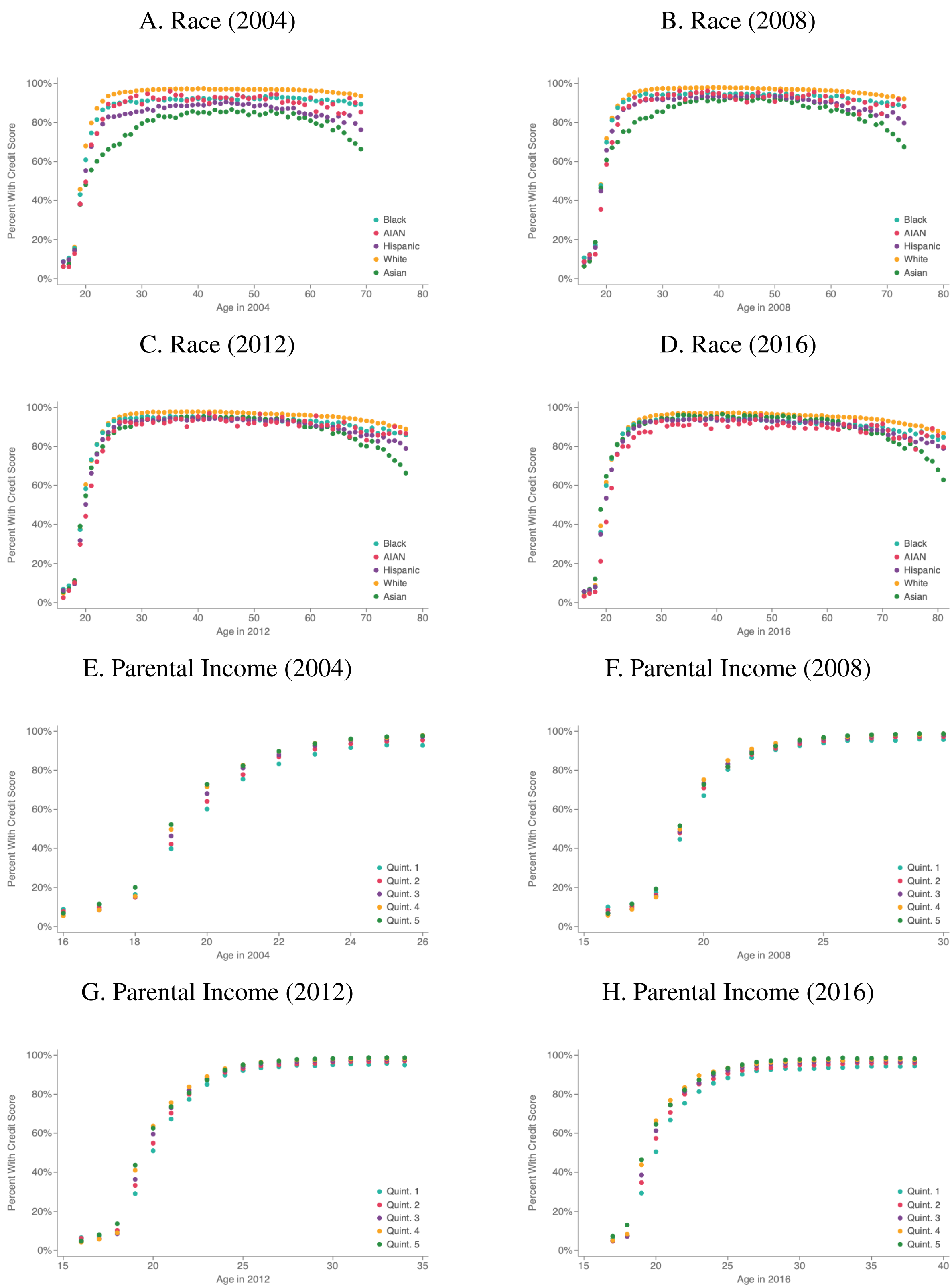
at other institutions, stocks and mutual funds, assets in IRA or KEOGH accounts, assets in 401k or thrift savings accounts, and other assets. Before 2014, there was only one question that combined equity in rental properties or real estate other than the primary residence, while this was split into two questions afterwards. There was also a question added about education savings accounts, which was not included in panels before 2014. Respondents in these surveys have been assigned PIKs by PVS based on name, address, date of birth, and sex which allows us to link to the rest of our datasets. We use weights provided in the SIPP. Because the SIPP is focused on program participation, the survey uses a complex, two-stage sample design, with an oversampling of households from counties (or clusters of low population counties) with a high concentration of low-income households. The weights then incorporate the probability of selection, an adjustment for subsampling within small county clusters, an adjustment for movers, a nonresponse component, and a post-stratification adjustment (U.S. Census Bureau, 2019).

A.C Prolific Survey

We administered a bespoke online instrument through Prolific Academic, a large opt-in research panel that recruits U.S. adults and compensates them for survey participation. We collected 754 complete responses from participants aged 22–30 who self-identified as either Black or White. To approximate the joint distribution of race $\times$ parental education in the ACS, we stratified recruitment targets by those two dimensions, but low-education Black respondents remain under-represented because they are relatively scarce in the Prolific pool. Overall, respondents are positively selected on socioeconomic status: 42% are male, 61% report at least one parent with a bachelor's degree, 48% percent hold a college degree themselves, and self-reported mean annual income is $74,457 among Black participants and $65,713 among White participants. After list-wise deletion for item non-response the analytic sample used in Table XI and Appendix Figure A.22 comprises 702 individuals.

The survey contains five modules. (i) Debt-repayment behavior: respondents separately indicate whether, in the past 12 months, they "missed or were late on a payment for any credit product (e.g., credit-card, auto, student loan)" and whether they "missed or were late on any household bill (e.g., phone, electricity, water, gas, medical)." We define our headline delinquency indicator as 1 if either answer is "yes;" 53% of the sample meets this criterion. (ii) Alternative financial services: usage of payday loans, payday apps, auto title loans, pawnshop credit, buy-now-pay-later (BNPL) plans, and rent-to-own contracts in the previous year (summary results in Table XI). (iii) Financial networks and shocks: frequencies and dollar amounts of transfers to and from friends or family, the maximum amount respondents believe they could borrow informally, and a checklist of unexpected expense categories (Appendix Figure A.22). (iv) Financial literacy: the canonical "Big 3" questions on compound interest, inflation, and diversification, replicating our NFCS and SCF analyses. (v) Background demographics: own education, sex, current income, the highest educational attainment of either parent (our principal proxy for class), and the ZIP Code of the home where the respondent lived during high school; the latter allows us to merge each individual to the county-level place-effects estimated from the credit bureau–tax–Census data.

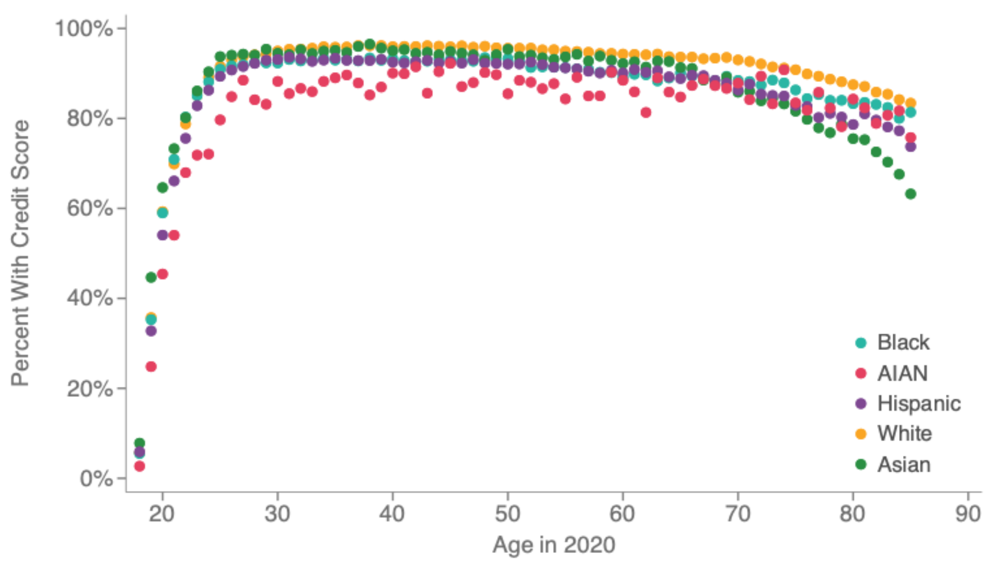
FIGURE A.1
Fraction with a Credit Score by Race/Parental Income and Age and Year



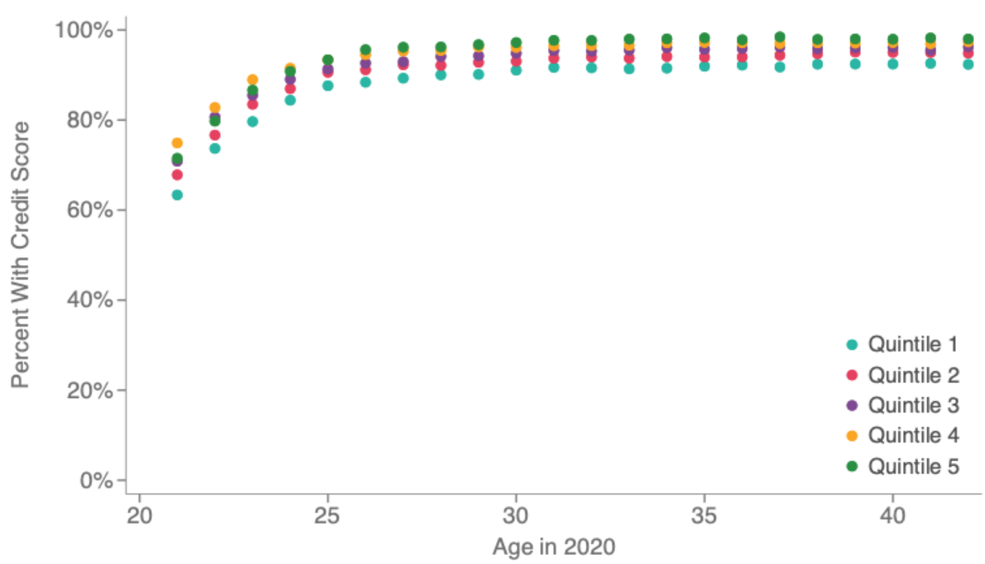
Notes: This figure presents the fraction of individuals in our population sample in different years who have a VantageScore 4.0. Panels A-D break this out by race and Panels E-H split by parental income.

FIGURE A.2
Percent with a VantageScore 4.0 Score by Age

A. Race

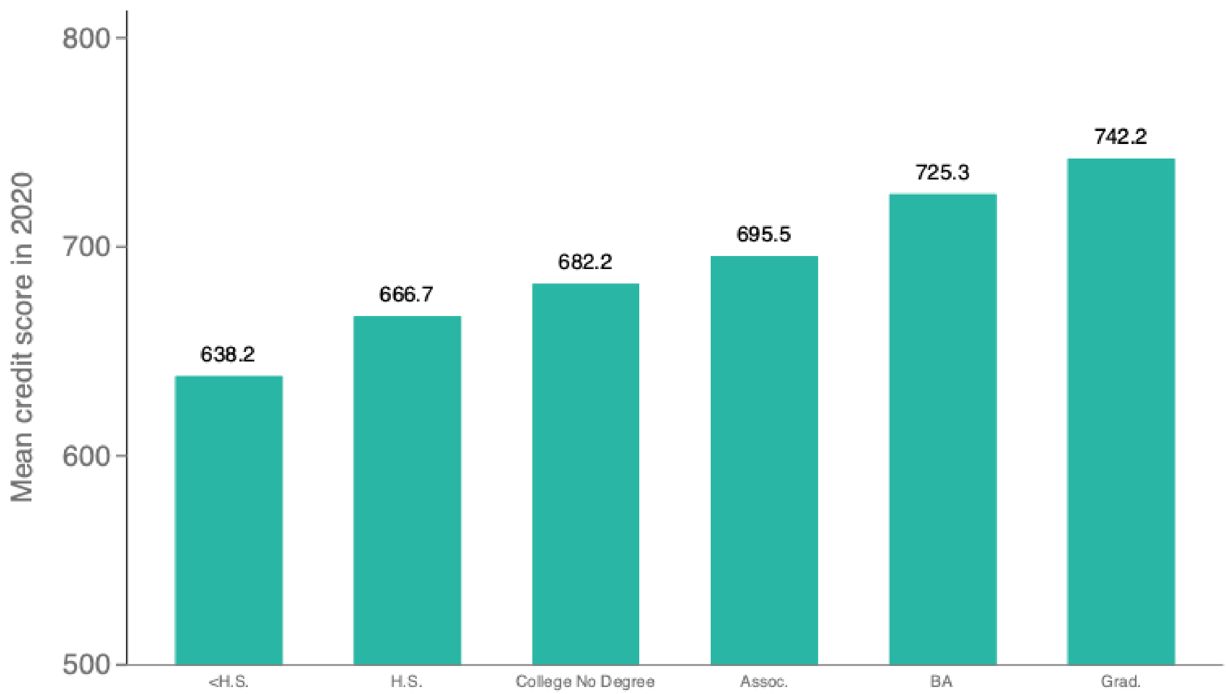


B. Parental Income Quintile



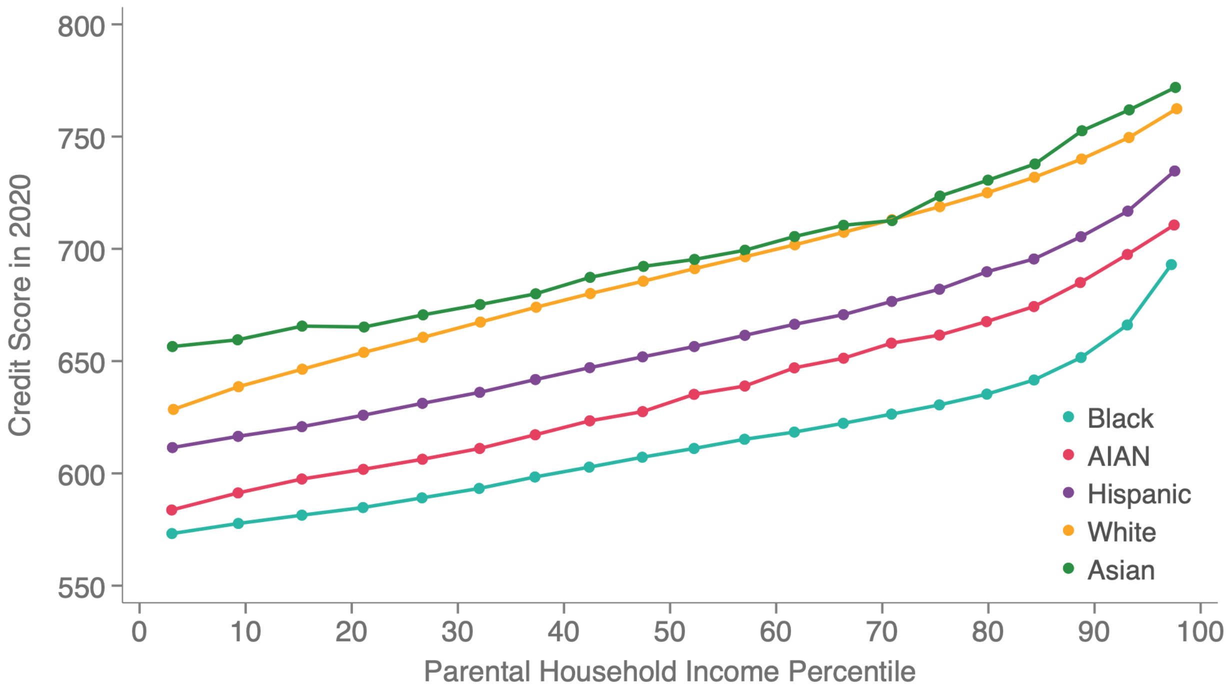
Notes: This figure presents the fraction of individuals in our population sample in 2020 who have a VantageScore 4.0 credit score. Panel A plots this rate by race. Panel B plots this rate by parental income quintile.

FIGURE A.3
Credit Scores by Parental Education



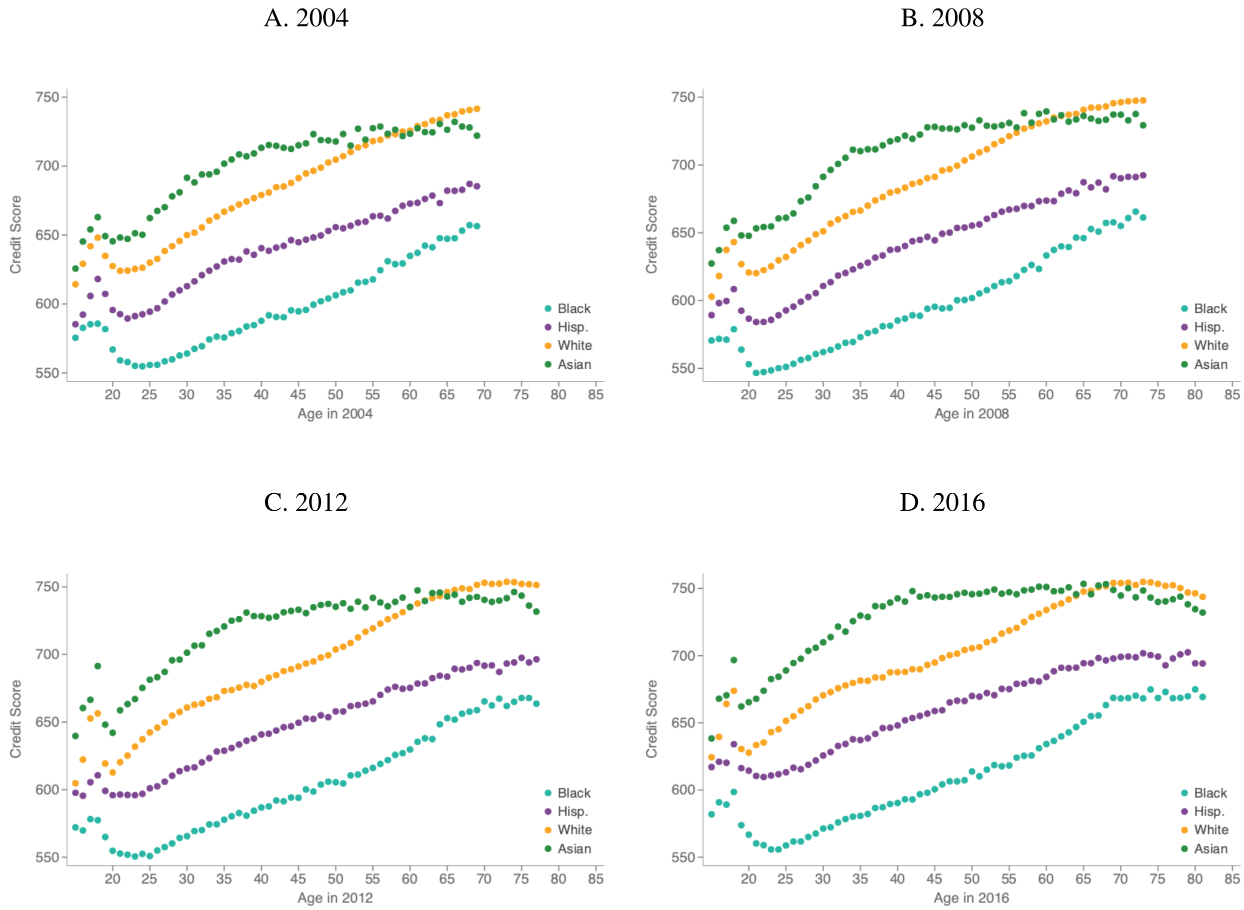
Notes: This figure presents the average credit scores in 2020 by parental education for our intergenerational sample (born between 1978 and 1985). We define parental education as the most education received by either parent from the ACS.

FIGURE A.4
Credit Scores by Race and Parental Income 2020, Children of Native-born Mothers



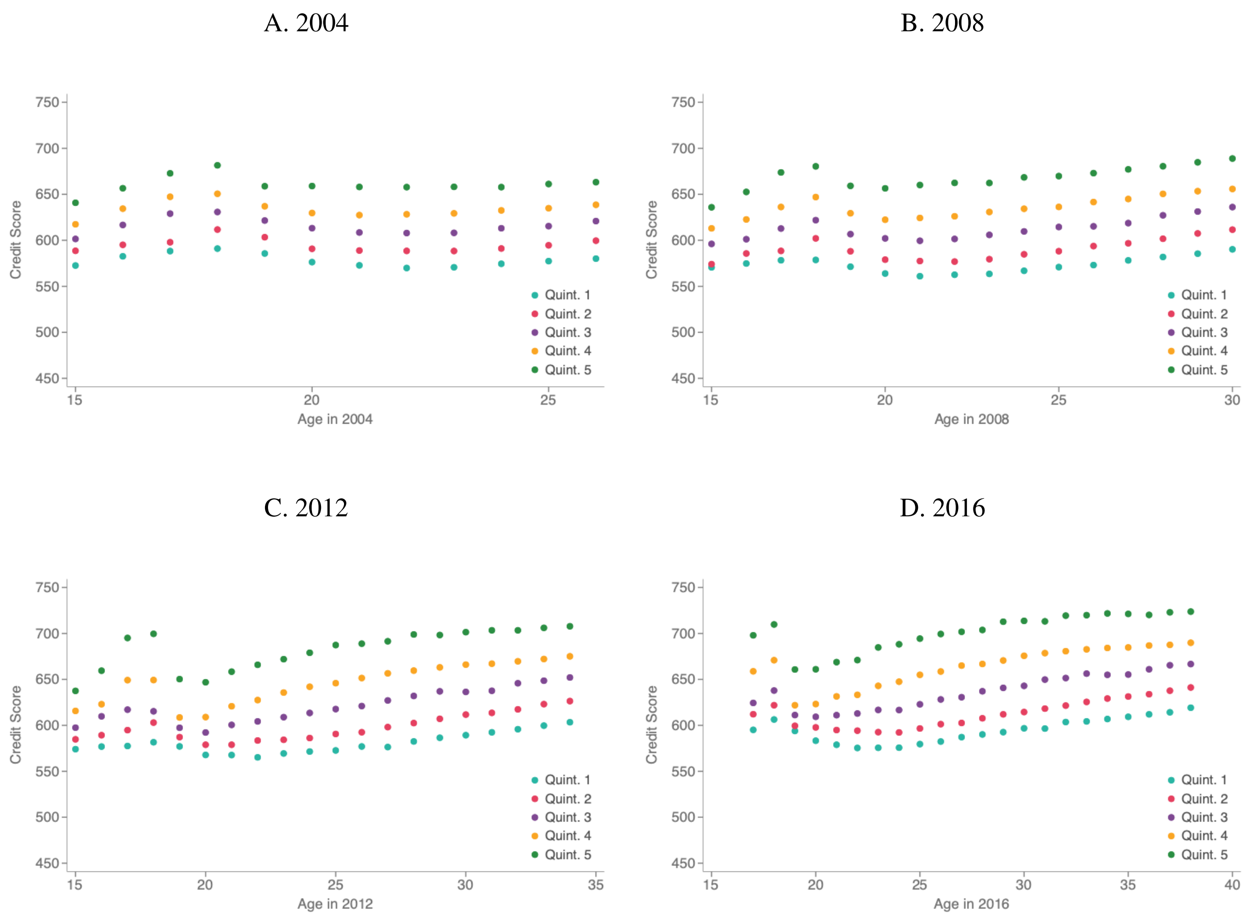
Notes: This figure presents the average credit scores in 2020 by race and parental income percentile as in Figure III, but restricts to the subset of children whose mothers were born in the U.S.

FIGURE A.5
Credit Scores by Age and Race, by Year



Notes: This figure presents the average credit score by age in years 2004, 2008, 2012, and 2016 by race.

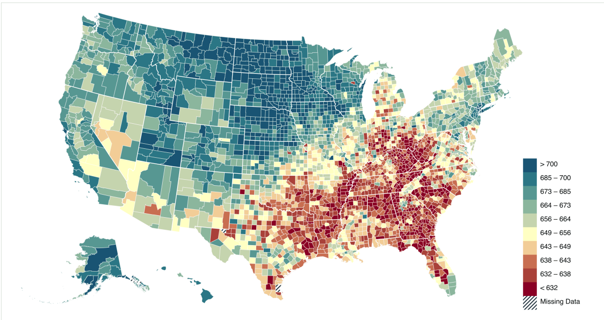
FIGURE A.6
Credit Scores by Age and Parental Income Quintile



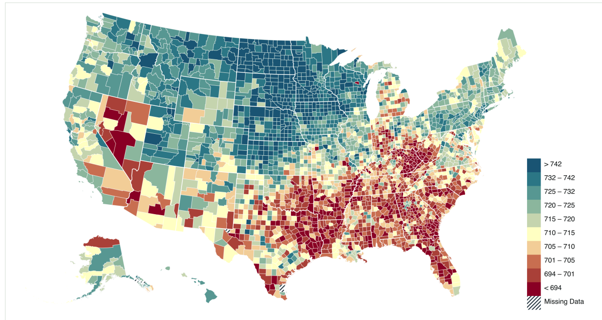
Notes: This figure presents the average credit score by age in years 2004, 2008, 2012, and 2016 by parental income quintile.

FIGURE A.7
Geography of Credit Scores by Race and Parental Income

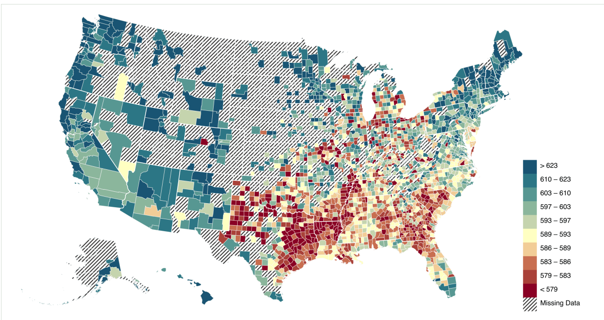
A. White, 25th Percentile Parental Income



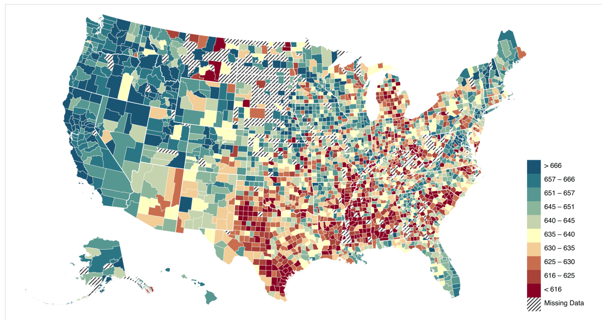
B. White, 75th Percentile Parental Income



C. Black, 25th Percentile Parental Income

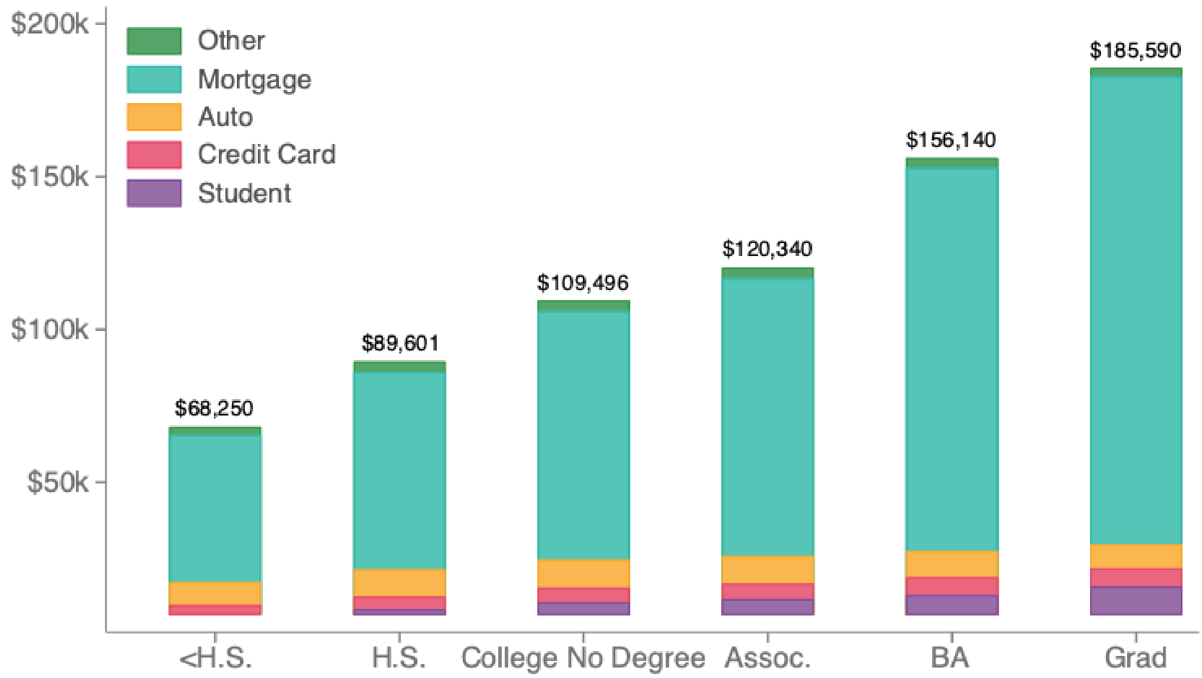


D. Hispanic, 25th Percentile Parental Income



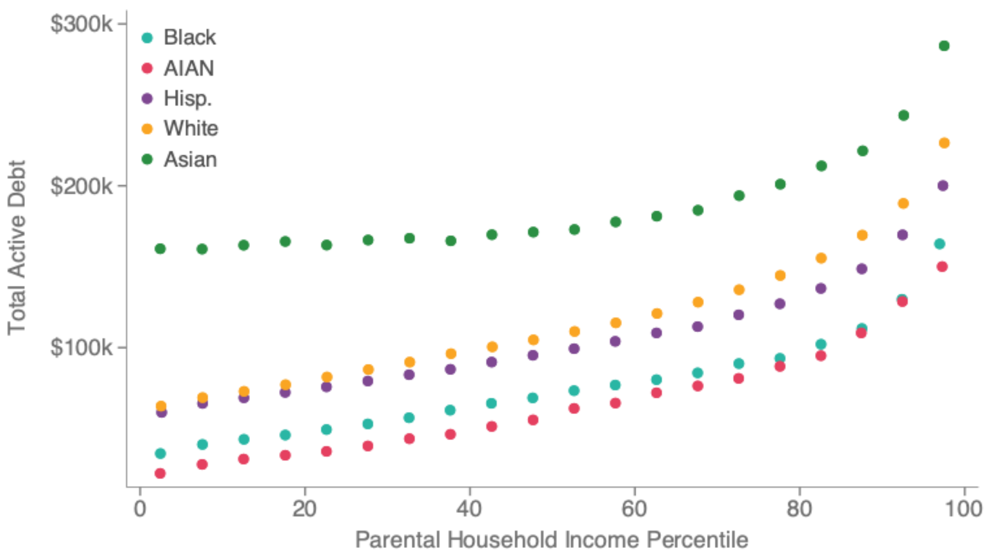
Notes: This figure presents maps of credit score in 2020 by county.

FIGURE A.8
Composition of Total Debt by Parental Education



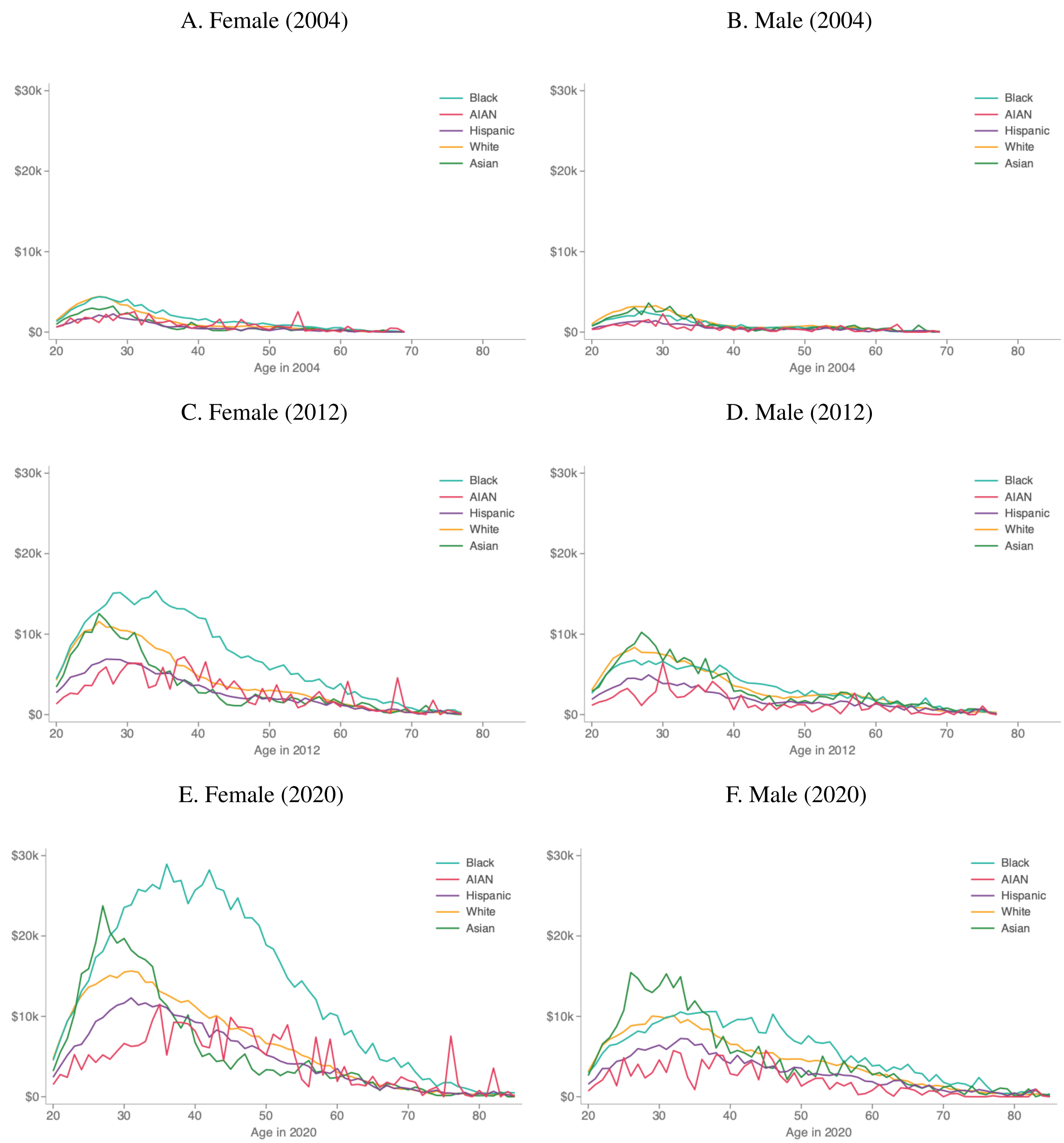
Notes: This figure presents a stacked bar chart of average debt holdings by type of credit split out by parental education. We present 4 credit types: mortgages, auto loans, credit card balances, and student loans, which comprise nearly all debt on credit reports.

FIGURE A.9
Total Debt by Race and Parental Income Percentile



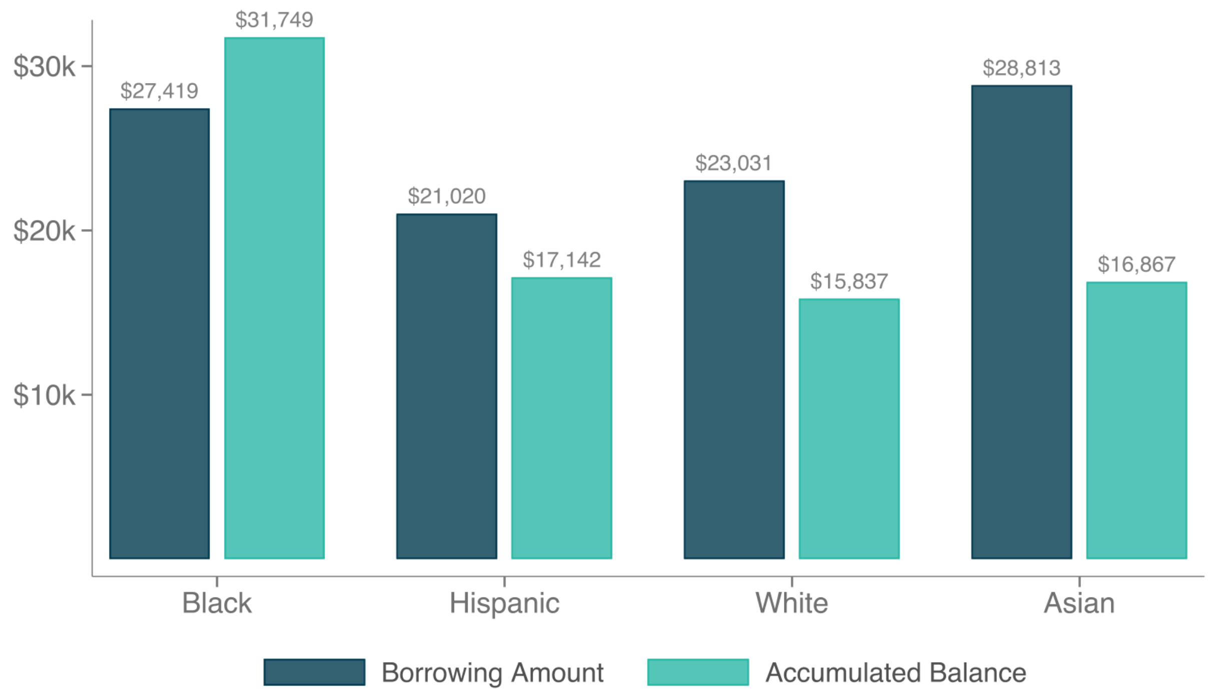
Notes: This figure presents a binned scatter plot of total active debt in 2020 on parental income percentile by race in our intergenerational sample (born between 1978 and 1985).

FIGURE A.10
Student Debt by Year and Race



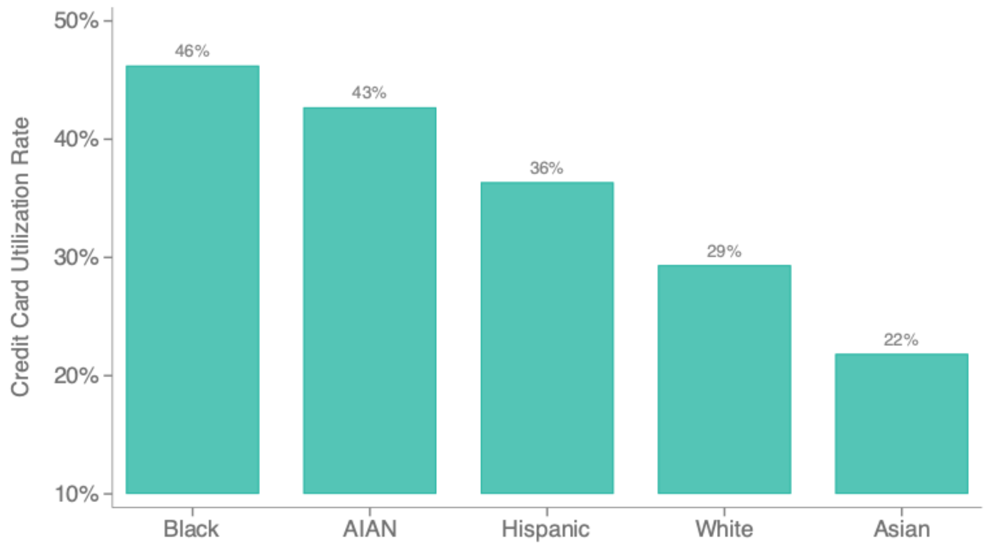
Notes: This figure presents the average student loan balance in our population sample by age broken out by year and sex.

FIGURE A.11
Student Debt Borrowing Amounts and Balances



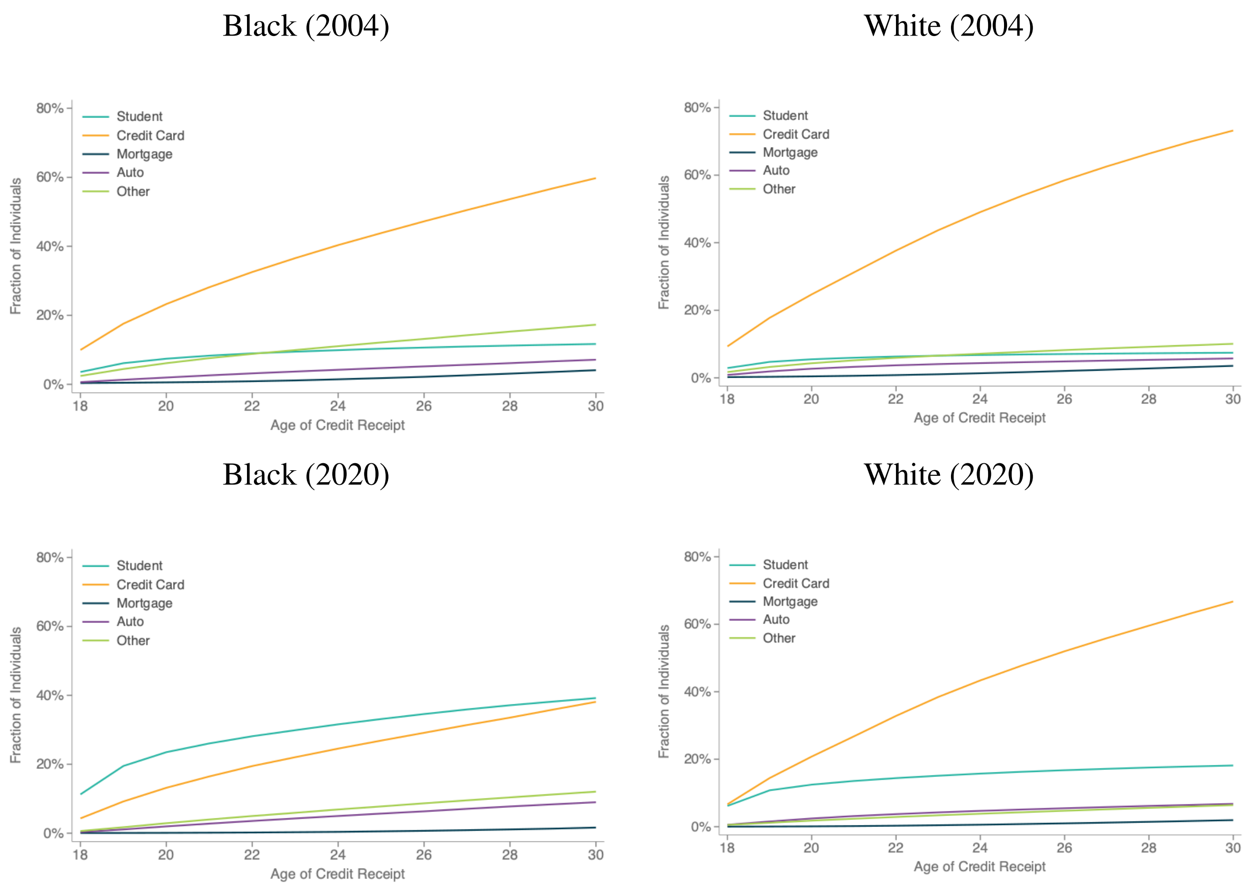
Notes: This figure plots average borrowing amounts and accumulated balances by race as of 2015 among student borrowers who entered college in 1996. Averages are calculated using data from the 1996 Beginning Postsecondary Students (BPS) study, which merges survey responses with administrative records for a representative sample of 12,400 first-time college enrollees.
Source: U.S. Department of Education, National Center for Education Statistics, 1996 Beginning Postsecondary Students (BPS) study, authors' calculations.

FIGURE A.12
Credit Card Utilization by Race



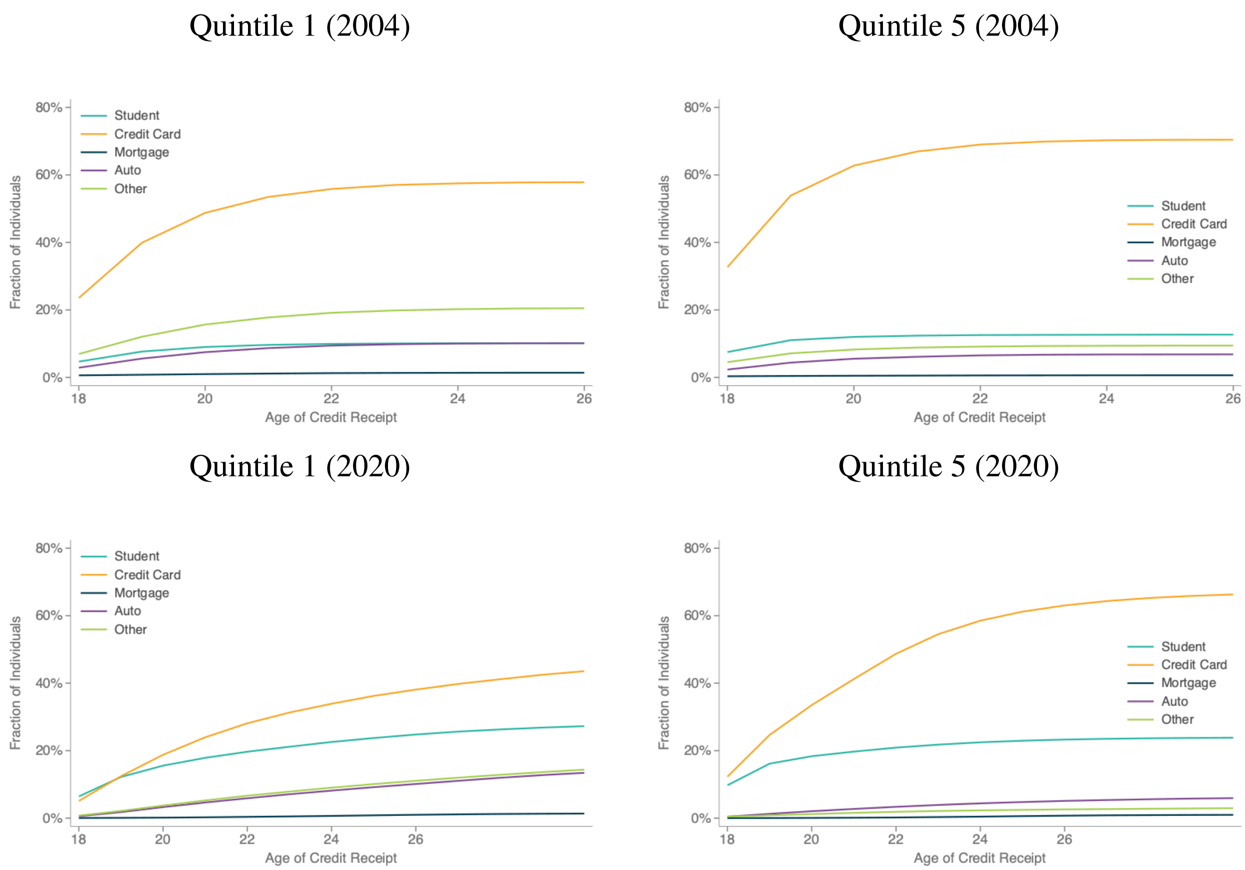
Notes: This figure presents the average individual level credit card utilization in our intergenerational sample (born between 1978 and 1985) in 2020 by race.

FIGURE A.13
Type of First Tradeline by Age and Race



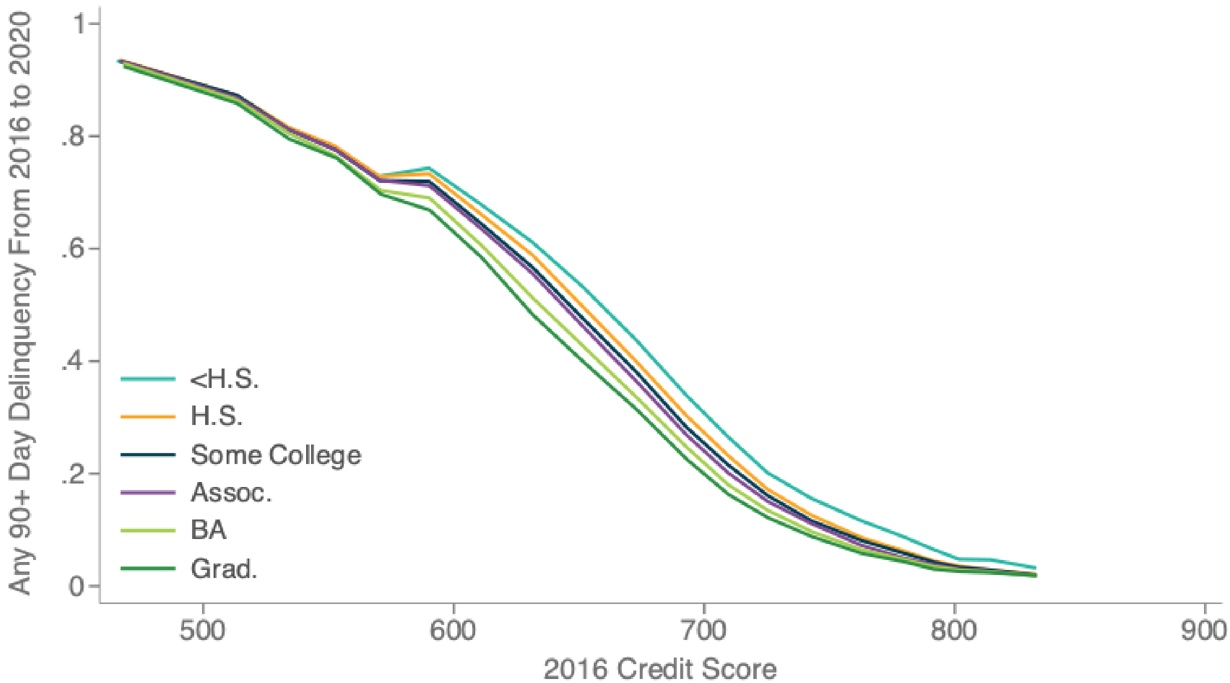
Notes: This figure presents the type of first tradeline by age using the population sample. For each individual, we measure the age at which they first obtained a tradeline in the credit file and the type of tradeline they received. Then, for each age, we plot the fraction of people whose first tradeline was a given type among those who have received a tradeline by that age. At older ages, the graph therefore presents the fraction of individuals in the population who received different types of credit as their first tradeline.

FIGURE A.14
Type of First Tradeline by Age, Parental Income



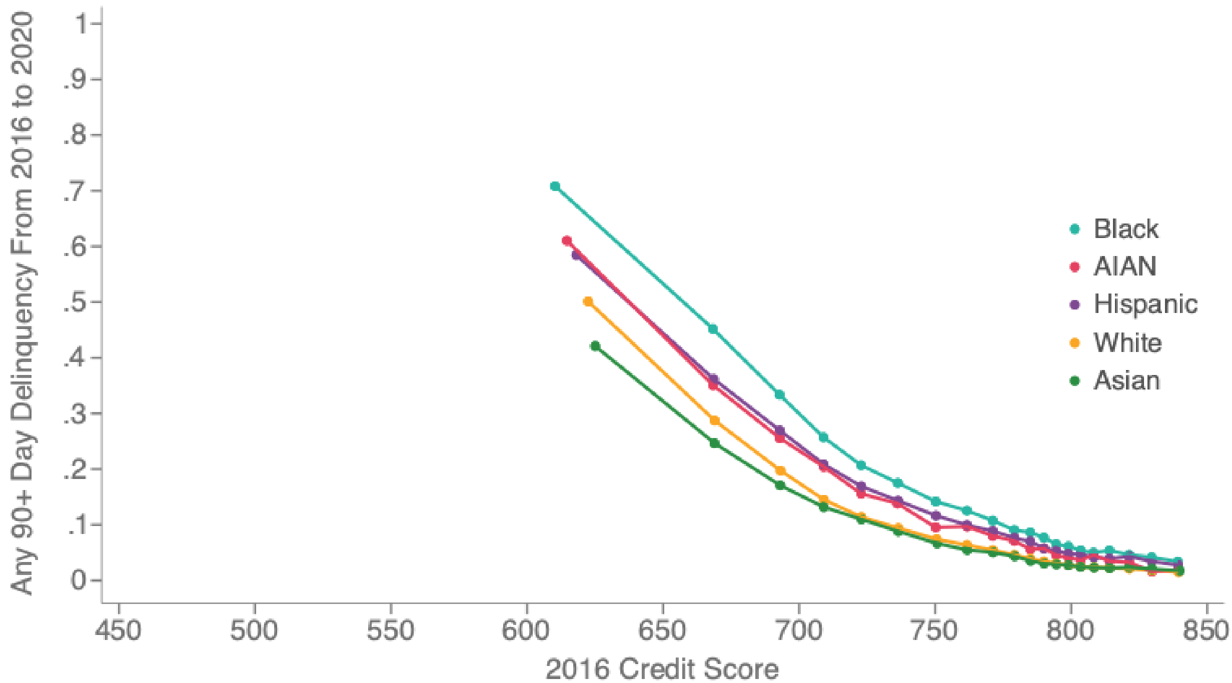
Notes: This figure presents the type of first tradeline by age and category of debt. For each individual, we measure the age at which they first obtained a tradeline in the credit file and the type of tradeline they received. Then, for each age, we plot the fraction of people whose first tradeline was a given type among those who have received a tradeline by that age. At older ages, the graph therefore presents the fraction of borrowers in the population who received different types of credit as their first tradeline.

FIGURE A.15
90+ Day Delinquency versus Credit Score by Parental Education



Notes: This figure presents the average 90+ day delinquency rate between 2016 and 2020 (using the 2020 credit file) as a function of the 2016 credit score on the horizontal axis, separately by parental education.

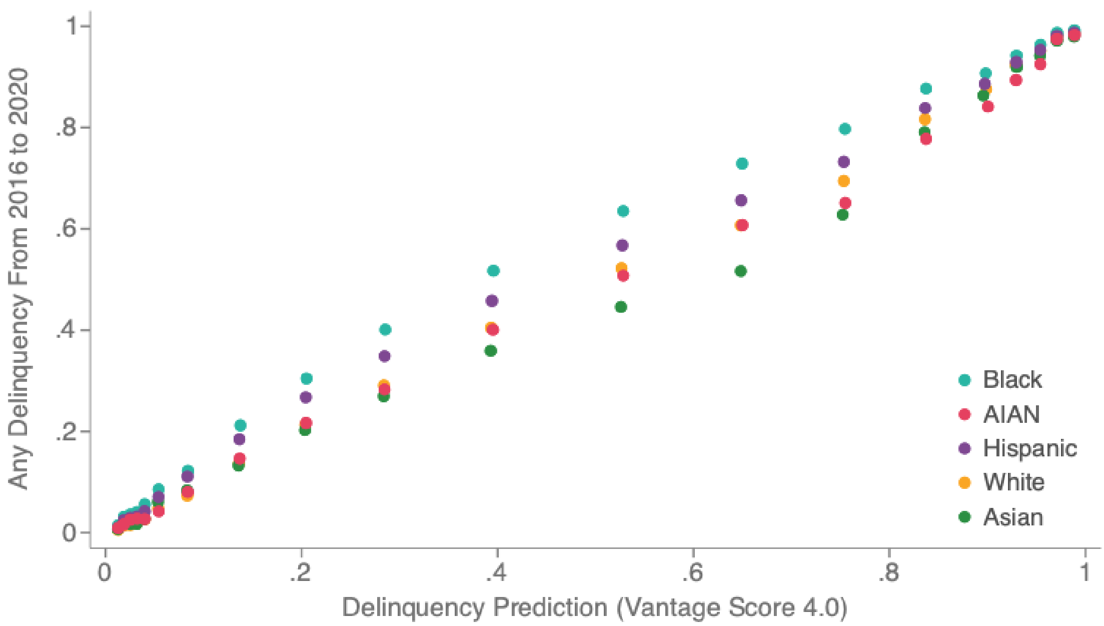
FIGURE A.16
90+ Day Delinquency versus Credit Score for Individuals with No Late Payments



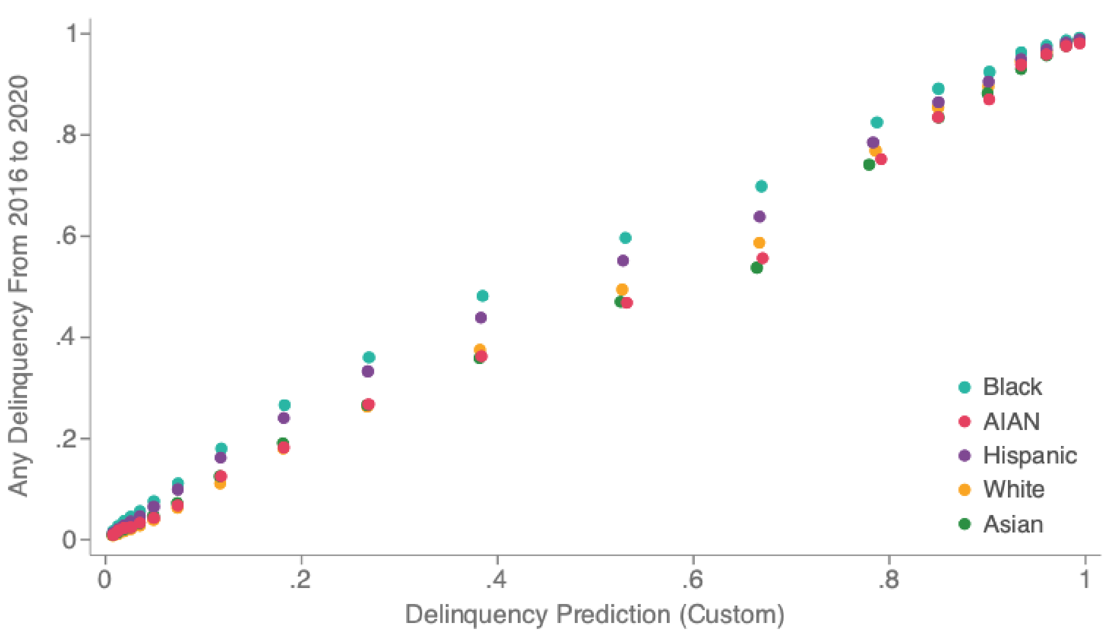
Notes: This figure presents the average 90+ day delinquency rate between 2016 and 2020 (using the 2020 credit file) as a function of the 2016 credit score on the horizontal axis, separately by race. We restrict the sample to individuals without any 30+ day late payment on their credit report in 2016.

FIGURE A.17
Alternative Delinquency Predictors

A. VantageScore 4.0

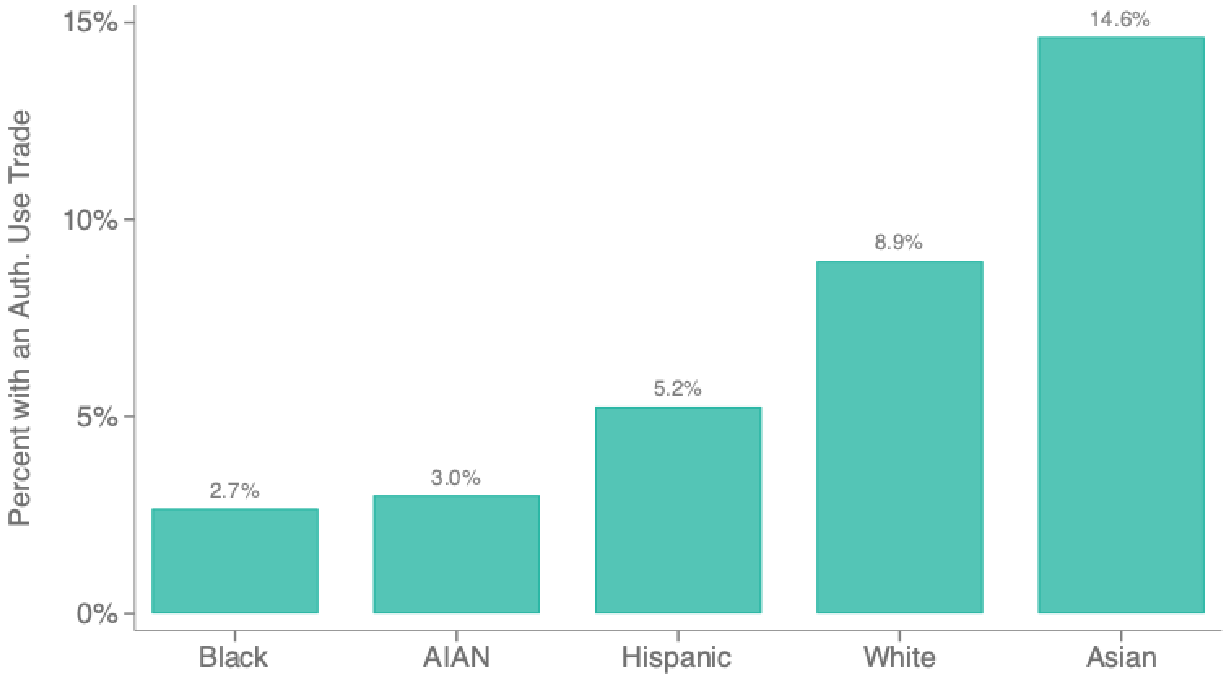


B. Custom Prediction



Notes: This figure compares our conclusions for calibration bias by race when using the VantageScore 4.0 score versus a simple logit regression using a vector of credit score attributes. The attributes include the VantageScore 4.0 score itself, as well as credit card, auto loan, student loan, and mortgage balances. The horizontal axis presents the predicted probability of observing a 90+ day late payment on the 2020 credit score as a function of the 2016 credit file information. Panel A uses the 2016 VantageScore 4.0 score to predict delinquency while Panel B uses our logit regression prediction using 2016 credit file variables, showing that the calibration bias patterns are similar when using other prediction algorithms from the information in the credit file.

FIGURE A.18
Incidence of Authorized User Trades

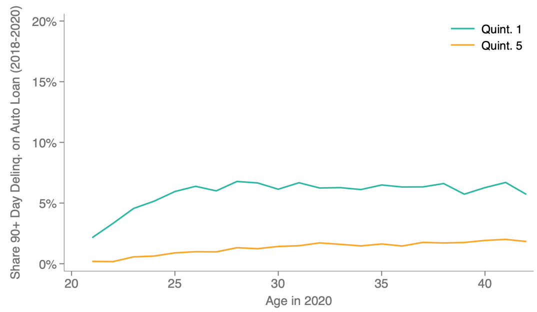


Notes: This figure presents percentage of individuals in our intergenerational sample (born between 1978 and 1985) in 2004 who have an authorized user trade by race.

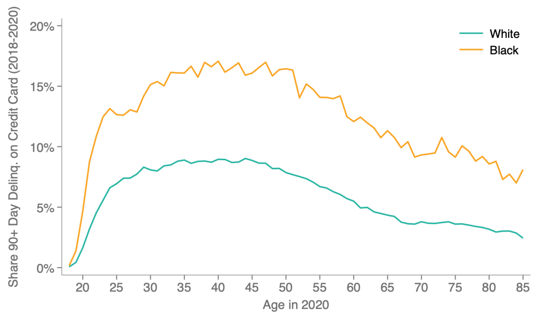
FIGURE A.19
90+ Day Delinquency By Tradeline By Age and Race/Parent Income Quintile

A. Auto Trades by Race

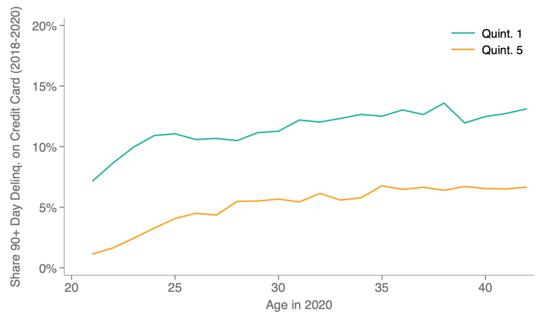
B. Auto Trades by Parental Income Quintile



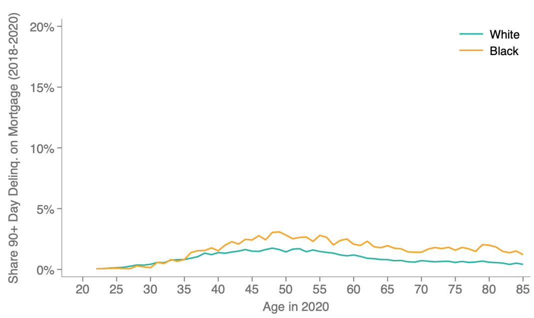
C. Credit Card Trades by Race



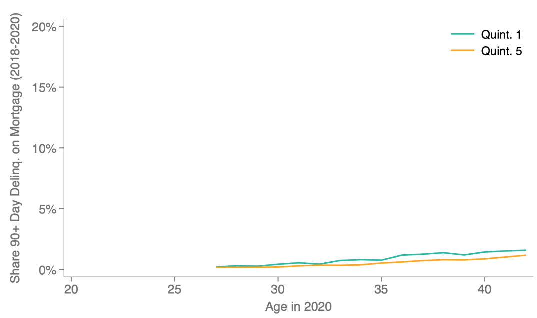
D. Credit Card Trades by Parental Income Quintile



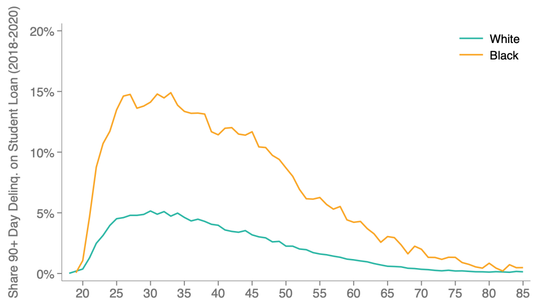
E. Mortgage Trades by Race



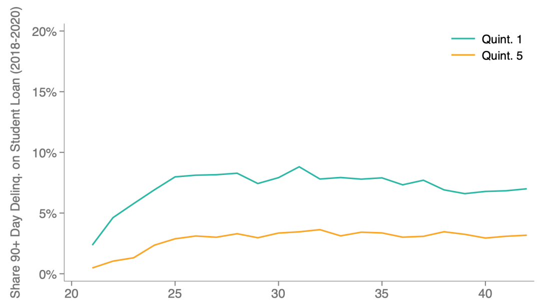
F. Mortgage Trades by Parental Income Quintile



G. Student Trades by Race

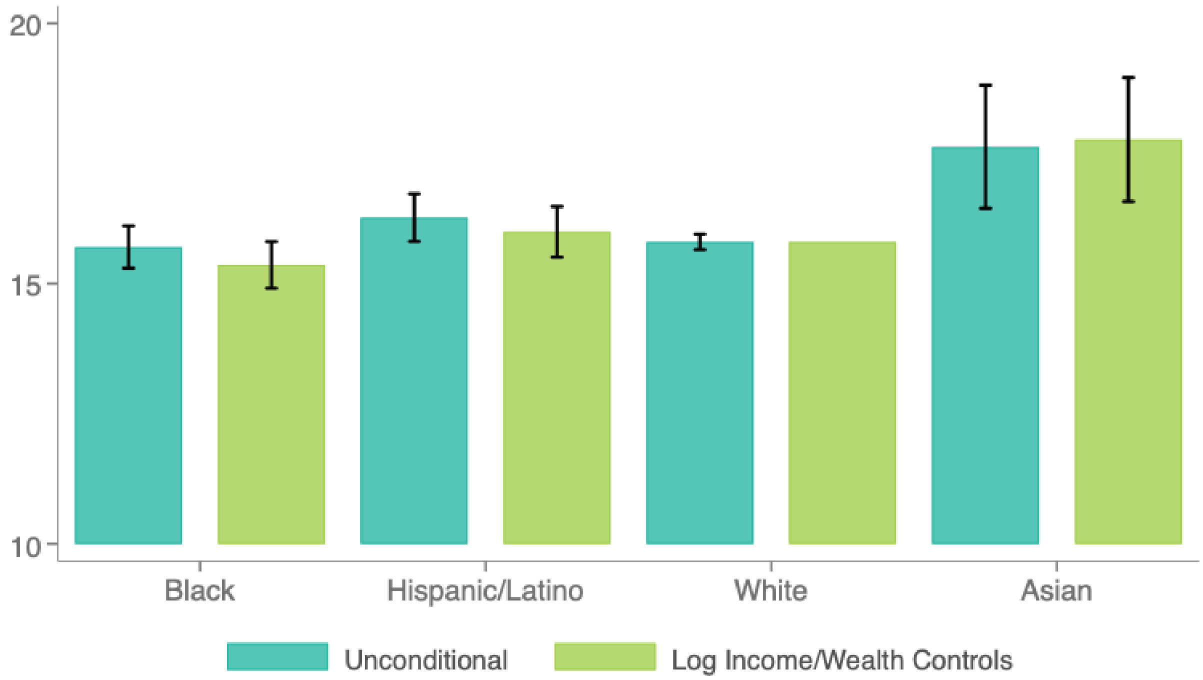


H. Student Trades by Parental Income Quintile



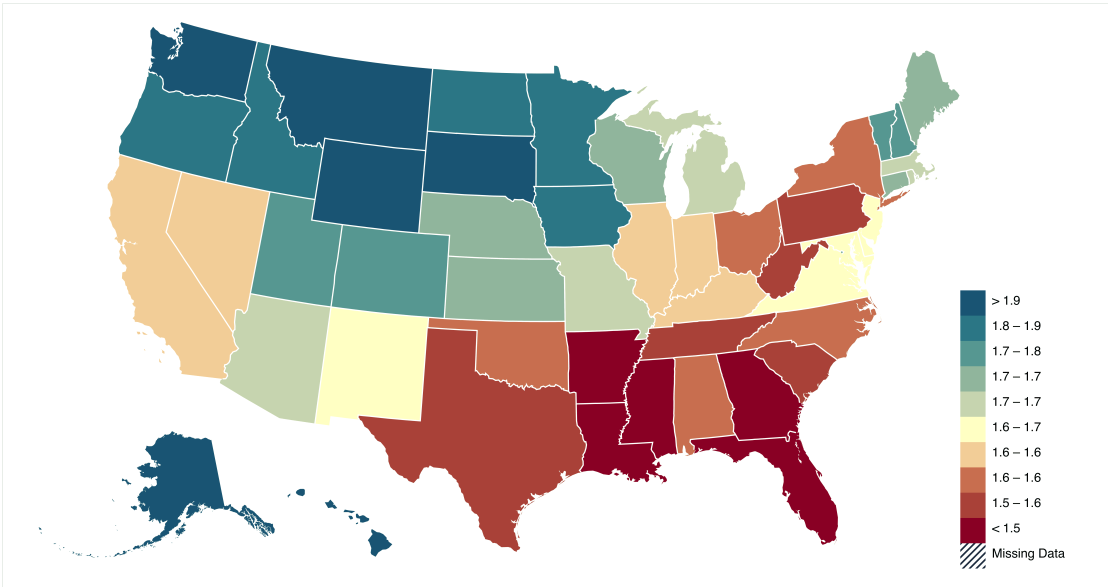
Notes: This figure presents the by tradeline 90+ day delinquency rates by race (left column) and parental income quintile (right column) in our population sample. Panels E and F (Mortgage Trades) starts at later ages due to an insufficient number of individuals with a mortgage delinquency for Census disclosure at younger ages.

FIGURE A.20
Credit Card Interest Rates by Race



Notes: This figure presents average credit card interest rates by race, pooling the 2013, 2016, 2019, and 2022 waves of the SCF. All regressions use SCF sample weights. "Unconditional" bars present raw means by race. "Log Income/Wealth Controls" bars are computed by taking the unconditional mean for White borrowers and then adding the coefficients on race dummy variables from a regression of credit card interest rates on race dummy variables (with White as the omitted category), log income, and log net wealth. Net wealth is computed following the method used for Federal Reserve Bulletin articles: https://www.federalreserve.gov/econres/files/bulletin.macro.txt. Excludes those who do not have a credit card or have a credit card with no interest rate.

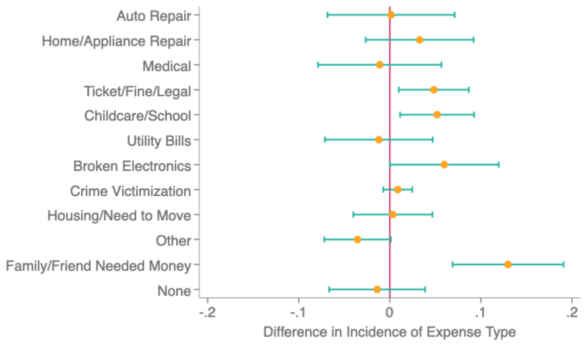
FIGURE A.21
"Big 3" Financial Literacy Score by State (NFCS)



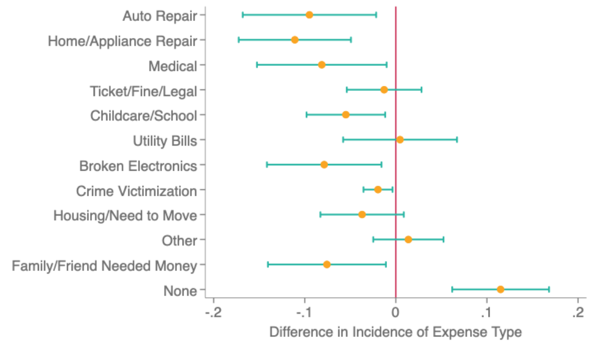
Notes: This figure reports the average score on the "Big 3" financial-literacy questions across U.S. states using the 2021 National Financial Capability Study (NFCS). For each respondent we count the number of correct answers to M6 (compound interest), M7 (inflation and real returns), and M10 (diversification), yielding a score from 0 to 3. Respondents saying "Don't know" or "Prefer not to say" are coded as incorrect. The NFCS sample includes adults aged 18 and older. We weight observations by the NFCS state weight wgt_s3, which re-weights the sample to be representative of each state's age-by-sex, race, and educational composition. The map shades each state according to its weighted mean score. This figure must be viewed in color. See Section II.C for survey details.

FIGURE A.22
Incidence of Types of Unexpected Expenses by Group (Prolific)

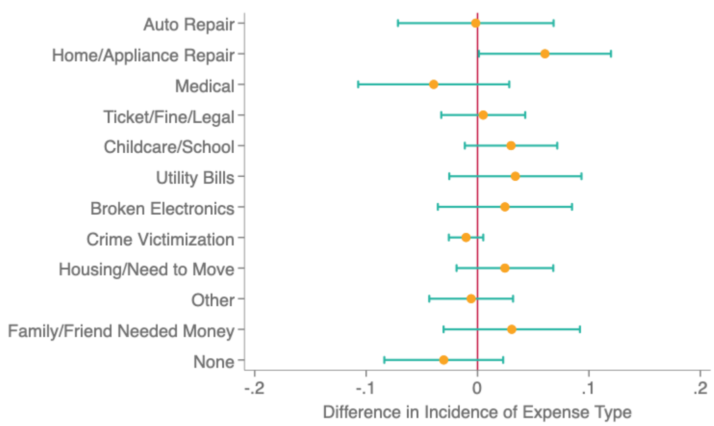
A. Black vs White



B. Low vs. High Parental Education

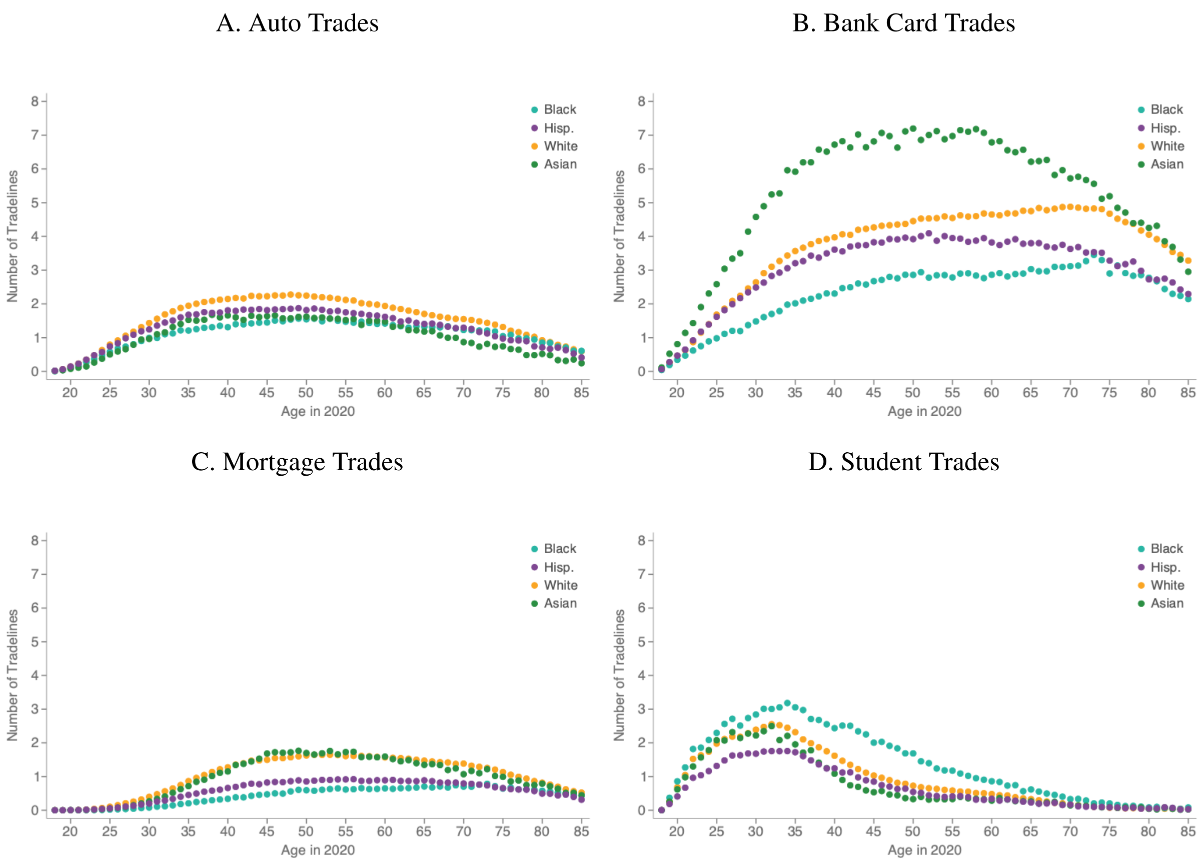


C. Low vs. High County-Level Repayment



Notes: This figure plots OLS point estimates and 95 percent confidence intervals from twelve separate linear-probability regressions—one for each category of unexpected expense—Auto repair; Home and/or appliance repair; Medical; Traffic ticket, fine, legal fee; Childcare or school expenses; High utility bills; Broken electronics (phone, computer, etc.); Identity theft/fraud/crime; Housing/needing to move; Other (please specify); Friend/family member needed money; None—on data from our Prolific sample of 702 U.S. adults aged 22–30. Each panel shows the estimated difference in the incidence of that expense type between two groups after controlling for household income: Panel A contrasts Black versus White respondents, Panel B contrasts respondents whose highest-educated parent has a high-school diploma or less with those whose parent has more education, and Panel C contrasts respondents from below-median versus above-median childhood-county debt-repayment areas. Points represent coefficient estimates and horizontal bars show ±1.96 standard-error intervals; a vertical red line at zero denotes parity. All regressions are unweighted, and standard errors are conventional OLS standard errors.

FIGURE A.23
Number of Tradelines by Age and Race



Notes: This figure presents the number of tradelines across different categories of debt in our population sample by race. We label Panel B "Bank Card Trades" instead of "Credit Card Trades" because the variable we use for the number of tradelines in this panel does not include retail credit cards, which are included in our other credit card variables.

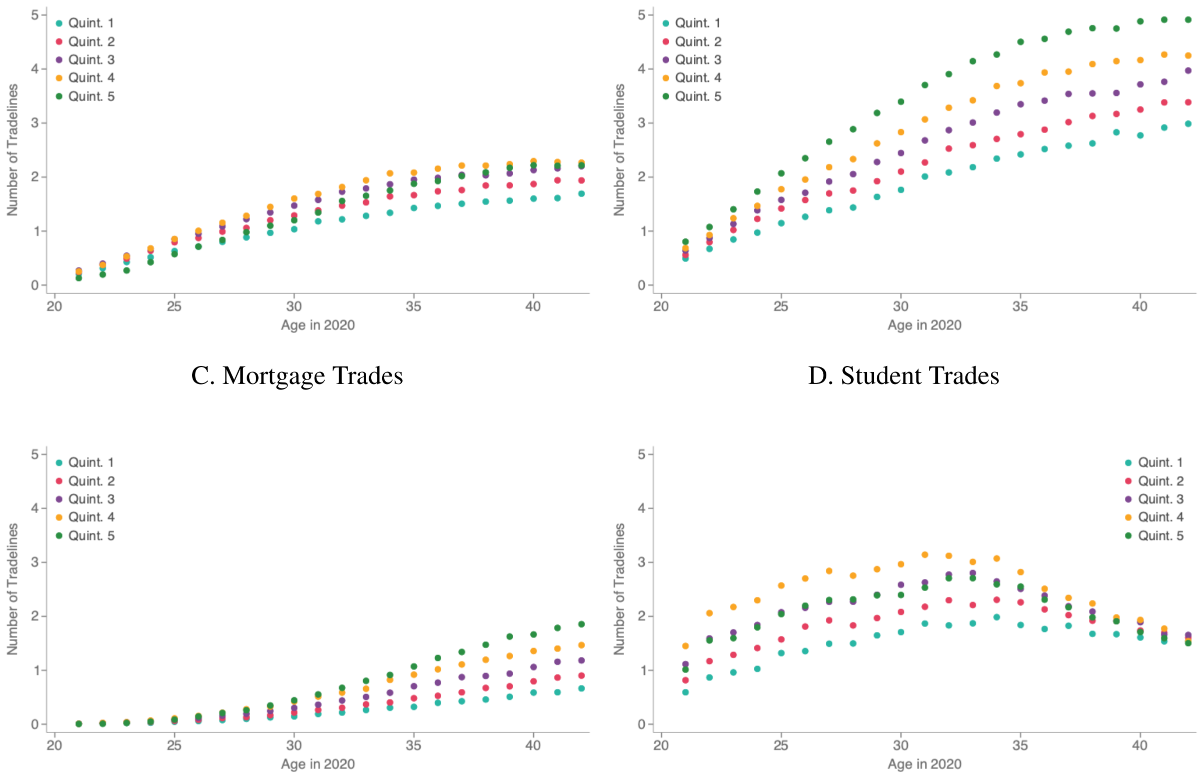
FIGURE A.24
Number of Tradelines by Age and Parental Income Quintile

A. Auto Trades

B. Bank Card Trades

C. Mortgage Trades

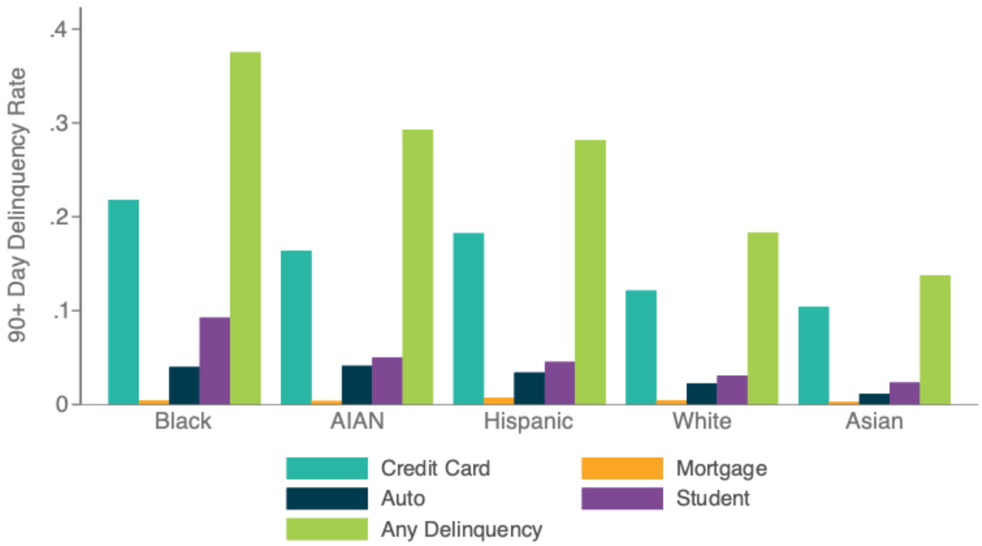
D. Student Trades



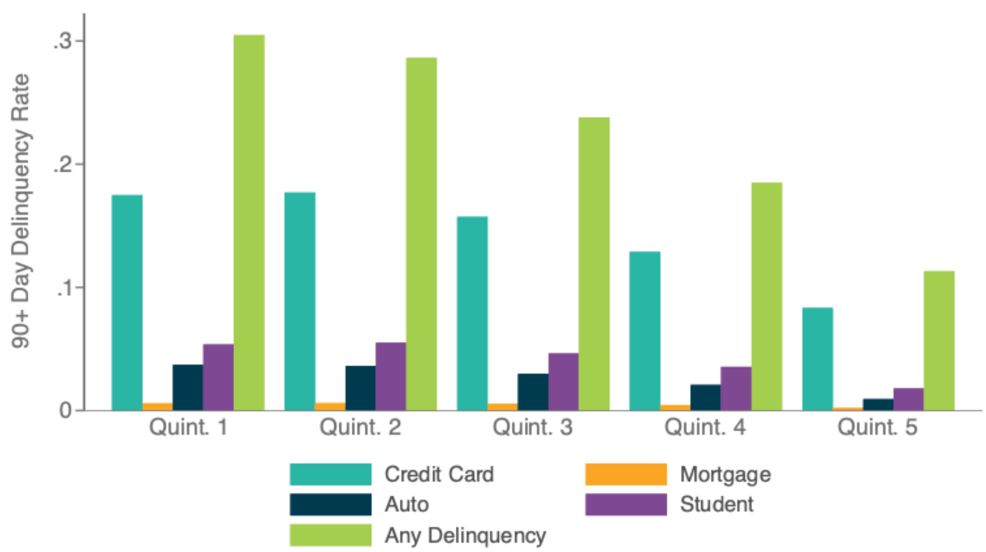
Notes: This figure presents the number of tradelines across different categories in our population sample by parental income. We label Panel B "Bank Card Trades" instead of "Credit Card Trades" because the variable we use for the number of tradelines in this panel does not include retail credit cards, which are included in our other credit card variables.

FIGURE A.25
90+ Day Late Payment Breakdown of 18-25 Yr Olds by Debt Type

A. Race



B. Parental Income Quintile



Notes: This figure shows the fraction of individuals in our intergenerational sample (born between 1978 and 1985) in 2004 who are 90+ day delinquent by the type of tradeline. Panel A breaks it out by race and Panel B breaks it out by parental income quintile.

TABLE A.1
Estimation of Median Credit Scores by Race/Ethnicity

Race	True Median	Zip Code Weighted By Population	Median Credit Score Mortgage Holders
Asian	779		781
Black	604	602	670
Hispanic	671	676	711
White	743	737	749

Notes: This table compares the estimates of the median credit score "True Median" from our population sample with estimates of the median credit score "Zip Code Weighted By Population" by race using ZIP codes where more than 60% of the population identifies as a given racial group. Due to small shares in most Zip Codes and mirroring the procedure in Garon (2022), we do not report an estimate for Asian individuals in the "Zip Code Weighted By Population" specification. The column "Median Credit Score Mortgage Holders" presents estimates of the median credit score by race among the sample of individuals who have a positive mortgage balance in 2012, but who do not have a mortgage balance in 2008. This attempts to approximate the sample of individuals in Table I of Fuster et al. (2022).

TABLE A.2
Average Credit Card Credit Limits by Race

	(1)	(2)	(3)
	Credit Limit	Credit Limit	Credit Limit
Black	–15,788***	–11,088***	–8,019***
	(471)	(514)	(485)
Hispanic	–13,729***	–10,347***	–8,115***
	(587)	(583)	(574)
Asian	17,404***	13,119***	12,978***
	(5,105)	(4,728)	(4,692)
Log Income		8,881***	7,545***
		(484)	(477)
Log Wealth			1,028***
			(66)
Delinquent			–829***
			(113)
N	21,645	21,645	21,645
R^2	0.038	0.132	0.160
Quadratic Age Control			X
White Mean	23,313		

Notes: This table reports OLS regression estimates of racial differences in total credit card credit limits, pooling the 2013, 2016, 2019, and 2022 waves of the SCF. The sample is restricted to respondents who report at least one credit card and provide a non-missing limit amount; observations are weighted by the SCF household sampling weight x42001 (implicate 1), yielding 21,645 observations. Column 1 regresses the aggregate credit limit on dummies for Black, Hispanic, and Asian borrowers (non-Hispanic White omitted). Column 2 adds log household income, and Column 3 further includes log household net wealth, an indicator for having been delinquent on any debt in the past year, and a quadratic in age (the "Quadratic Age Control" row marks their inclusion). Net wealth is computed following the method used for Federal Reserve Bulletin articles: https://www.federalreserve.gov/econres/files/bulletin.macro.txt. Standard errors, shown in parentheses, are conventional weighted-OLS standard errors. Statistical significance is denoted *** p < 0.01, ** p < 0.05, * p < 0.10.

TABLE A.3
Differences in Average Interest Rate by Race and Tradeline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Credit Card	Auto Loan	Mortgage	Credit Card	Auto Loan	Mortgage	Credit Card	Auto Loan	Mortgage
Black	–0.098	2.727***	0.726	–0.179	2.325***	0.657	–0.494**	1.679***	0.360
	(0.221)	(0.249)	(0.539)	(0.222)	(0.251)	(0.538)	(0.227)	(0.244)	(0.603)
Hispanic	0.467*	1.375***	0.685	0.404*	1.060***	0.608	0.203	0.730***	0.657
	(0.245)	(0.241)	(0.695)	(0.245)	(0.242)	(0.703)	(0.248)	(0.238)	(0.731)
Asian	1.827***	–1.434***	–1.930***	1.911***	–0.819	–1.648***	1.976***	–0.758	–1.509***
	(0.609)	(0.506)	(0.416)	(0.608)	(0.516)	(0.411)	(0.596)	(0.500)	(0.355)
Log Income				–0.204***	–1.132***	–0.219	–0.127**	–0.876***	–0.205
				(0.051)	(0.140)	(0.149)	(0.053)	(0.122)	(0.139)
Log Wealth							–0.081***	–0.185***	–0.093
							(0.018)	(0.020)	(0.065)
Delinquent							0.188***	0.478***	0.142
							(0.057)	(0.063)	(0.145)
Age Control							X	X	X
White Mean	15.800	5.360	5.549						
N	15,356	5,918	365	15,356	5,918	365	15,356	5,918	365
R^2	0.002	0.036	0.015	0.003	0.080	0.027	0.008	0.130	0.060

Notes: This table reports OLS regression estimates of racial differences in the interest rates paid on three common credit products, pooling the 2013, 2016, 2019, and 2022 waves of the SCF. Each column is restricted to respondents who report holding the indicated tradeline and have a non-missing annual percentage rate (APR); observations are weighted by the SCF household sampling weight x42001 (implicate 1). Columns 1–3 regress the APR on dummies for Black, Hispanic, and Asian borrowers (non-Hispanic White omitted). Columns 4–6 add log household income, and Columns 7–9 further include log household net wealth, an indicator for having been delinquent on any debt in the past year, and a quadratic in age. Net wealth is computed following the method used for Federal Reserve Bulletin articles: `https://www.federalreserve.gov/econres/files/bulletin.macro.txt`. The bottom panel shows the mean APR for White borrowers on each credit product. Standard errors, reported in parentheses, are conventional weighted-OLS standard errors. Statistical significance is denoted *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE A.4
Relationship Between 90+ Day Delinquency and Race/Class (2020)

Panel A: No Credit Score Control							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	0.291***	0.212***	0.199***	0.202***	0.241***	0.207***	0.189***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.027)	(0.001)	(0.001)
Asian	-0.172***	-0.129***	-0.106***	-0.096***	-0.009	-0.012***	-0.007***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.044)	(0.001)	(0.001)
Hispanic	0.086***	0.064***	0.060***	0.060***	0.068***	0.082***	0.064***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.025)	(0.001)	(0.001)
Parent Inc.	-0.394***	-0.230***	-0.187***	-0.181***	-0.098***	-0.084***	-0.067***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.030)	(0.001)	(0.001)
R^2	0.125	0.222	0.251	0.254	0.288	0.125	0.219
Panel B: With Credit Score Control							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	0.074***	0.072***	0.074***	0.074***	0.119***	0.092***	0.084***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.001)	(0.001)
Asian	-0.028***	-0.028***	-0.016***	-0.016***	0.031	0.007***	0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.039)	(0.001)	(0.001)
Hispanic	0.024***	0.023***	0.024***	0.024***	0.047**	0.035***	0.028***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.001)	(0.001)
Parent Inc.	-0.059***	-0.053***	-0.043***	-0.043***	-0.035	-0.018***	-0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.027)	(0.001)	(0.001)
N (100s)	254,600	254,600	254,600	254,600	42	15,580	13,640
R^2	0.448	0.448	0.457	0.457	0.442	0.324	0.389
Inc. 2016		X	X	X	X	X	X
Inc. Vec.			X	X	X	X	X
Def. Comp.				X	X	X	X
Home Equity				X	X	X	X
Liquid Assets					X		
Net Wealth					X		
Employer FE							X
Sample	All	All	All	All	SIPP	Stable	Stable

Notes: This table reports results from ordinary least squares (OLS) regressions of 90+ day delinquency between 2016 and 2020 on race and parental income rank, with and without controlling for credit score, across different samples and model specifications. All specifications use our intergenerational sample. Panel A presents estimates without credit score as a covariate; Panel B includes 2016 credit score as an additional control. Each column cumulatively adds the controls listed at the bottom of the table. The unit of observation is the individual. Coefficients are reported with standard errors in parentheses. Sample restrictions are defined in the last row: "SIPP" refers to individuals matched to the SIPP sample; "Stable" refers to individuals whose household income rank remains within ten percent of their 2015 rank, who remain with the same employer from 2015 to 2021. Column 7 adds an additional sample restriction of stable marital status from 2015 to 2021. We note that in column 2 the coefficient on household income rank in 2016 is -0.60 in Panel A and -0.057 in Panel B.

TABLE A.5
Parent Credit Score Predicts Child Delinquency (2020)

	(1)	(2)	(3)	(4)	(5)
			90+ Day Delinquency		
Parent Credit Score Rank 2004	-0.641***	-0.437***	-0.367***	-0.356***	-0.333***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Income Rank in 2016		-0.608***	-0.583***	-0.534***	-0.528***
		(0.001)	(0.001)	(0.001)	(0.002)
Parent Income Rank			-0.136***	-0.128***	-0.076***
			(0.001)	(0.001)	(0.002)
Wealth				X	X
Parent Education					X
N	4,147,000	4,147,000	4,147,000	4,147,000	1,050,000
R^2	0.102	0.209	0.214	0.218	0.214

Notes: This table presents a regression of any delinquency from 2016 to 2020 on parental credit score rank in 2004. Column 1 reports a univariate regression of delinquency on parental credit score rank. The next columns add controls. Column 2 adds child income in 2016. Column 3 adds parental income rank. Column 4 adds savings, which is the sum of deferred compensation from 2005 to 2016 and housing wealth. Column 5 adds parental education fixed effects.

TABLE A.6
Financial Literacy by Group (Prolific Survey)

	(1)	(2)	(3)	(4)
	Credit Report Duration	Correct Duration	Missed Payment	Missed Payment
Black	–0.975***	–0.060*	0.111***	0.098**
	(0.240)	(0.036)	(0.040)	(0.042)
Parent Education	–0.062	–0.011	–0.014*	–0.009
	(0.047)	(0.007)	(0.007)	(0.008)
Chldhd Cnty Repayment Rate	3.321**	0.159	–0.449**	–0.516**
	(1.361)	(0.196)	(0.218)	(0.238)
Credit Report Duration				–0.015*
				(0.009)
Correct Duration				0.146***
				(0.056)
Education Controls	X	X	X	X
N	610	702	702	610
R^2	0.104	0.024	0.027	0.035

Notes: This table examines group differences in credit-report literacy and assesses whether those differences help explain differences in repayment using data from our Prolific sample of U.S. adults aged 22–30. Column 1 regresses the respondent's numeric belief about how many years a missed payment stays on one's credit report (coded 0.5, 2, 5, 7, or 11) on indicators for Black race, a continuous measure of parental education (11 years = less than high school, 12 = high school graduate, 14 = technical/community college, 16 = college graduate, 18 = master's degree, 20 = professional or doctoral degree), and the average debt-repayment rate in the respondent's childhood county, controlling for the respondent's own education; observations are limited to the 610 respondents who provided a numeric answer. Column 2 uses the full sample of 702 respondents and repeats the regression with the dependent variable equal to 1 if the respondent gave the correct answer ("7 years") and 0 otherwise, treating non-respondents as incorrect. Column 3 replicates Column 1 of Table X, regressing a missed-payment indicator on the same group variables and education controls. Column 4 adds the two literacy measures from Columns 1–2 to the repayment regression to test whether literacy accounts for group gaps. All regressions are unweighted ordinary least squares; standard errors in parentheses are conventional OLS standard errors. Statistical significance is denoted *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.