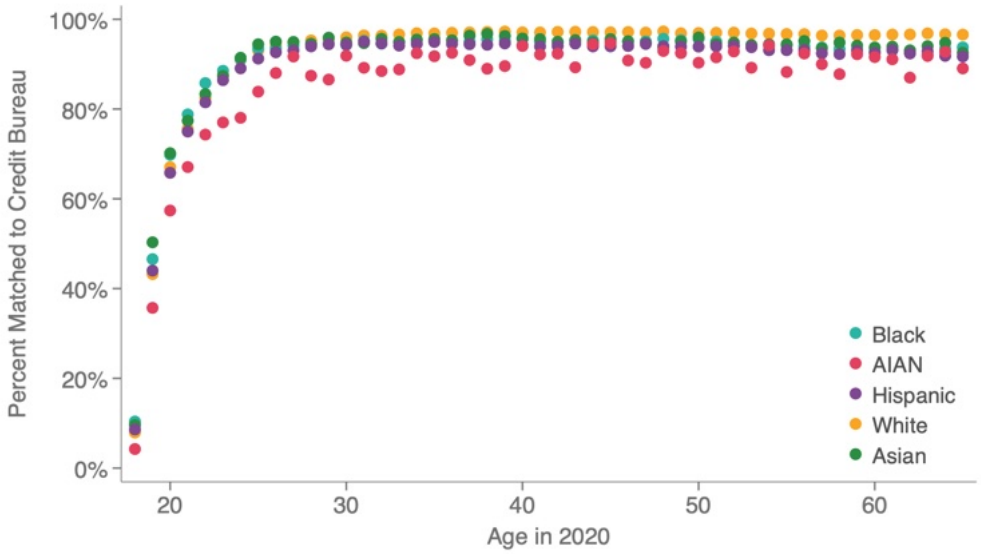
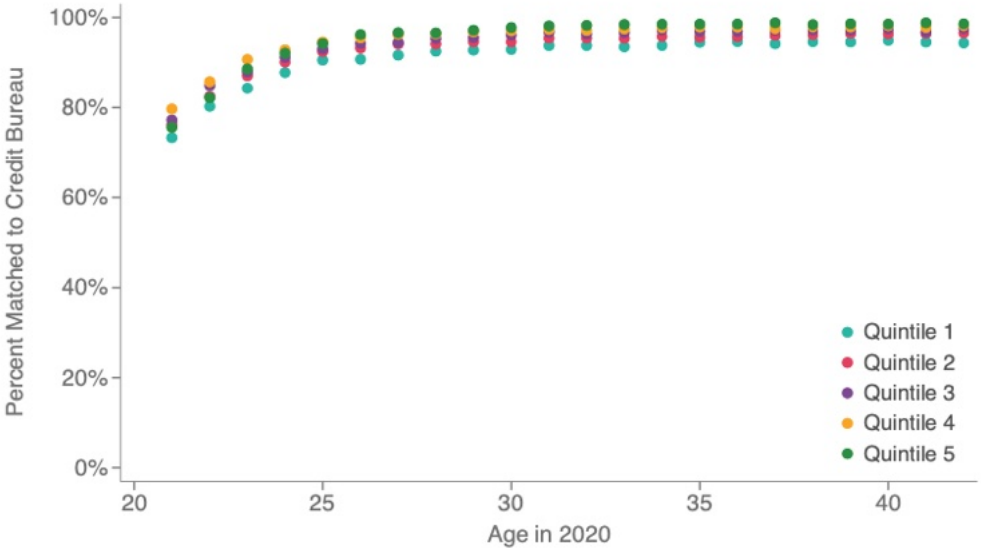
A Appendix Figures and Tables

FIGURE A.1
Percent of Population with Credit File by Age

A. Race



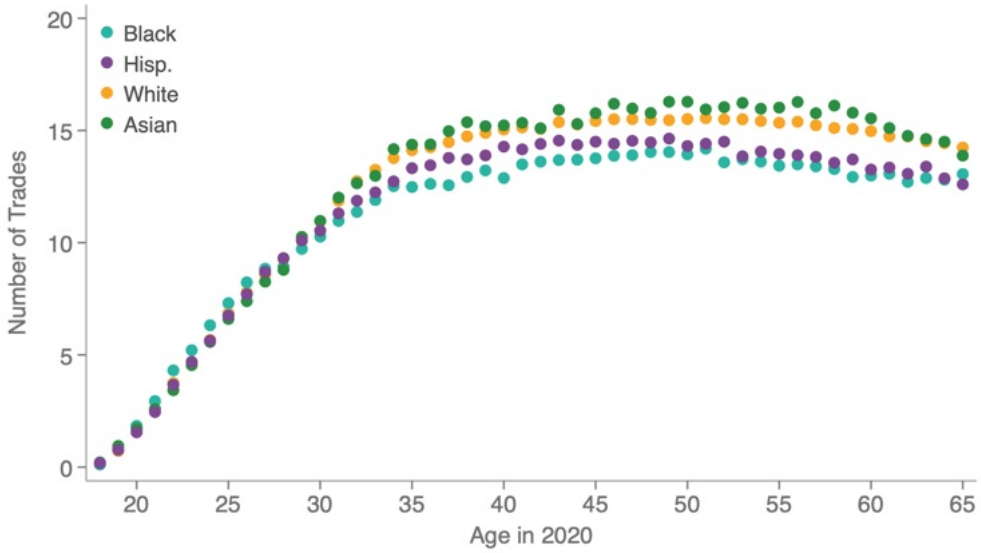
B. Parental Income Quintile



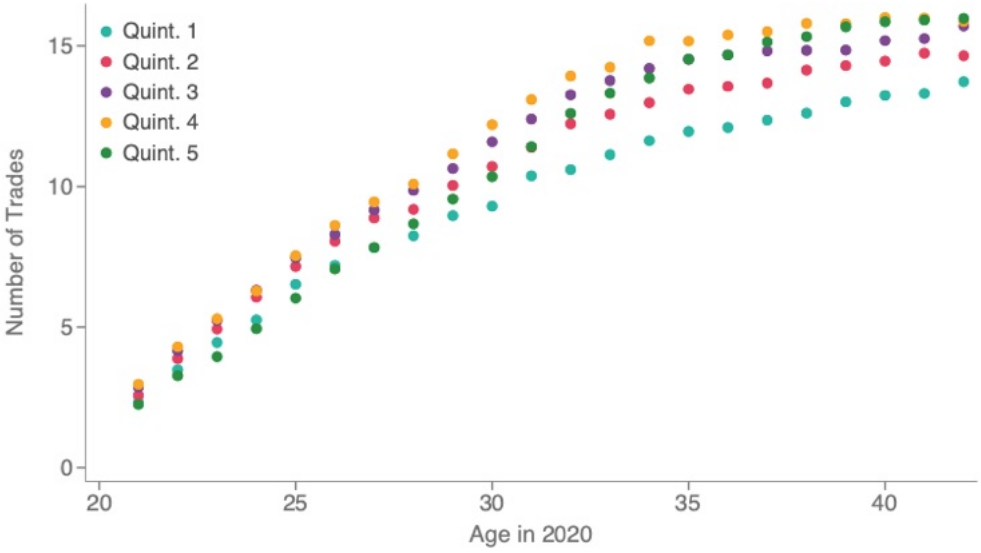
Notes: This figure presents the percentage of people in our population sample who have a credit file by age, race, and parental income in 2020. Panel A reports the percentage by age and race. Panel B reports the percentage by age and parental income quintile, restricting to the birth cohorts we are able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

FIGURE A.2
Number of Tradelines by Age

A. Race

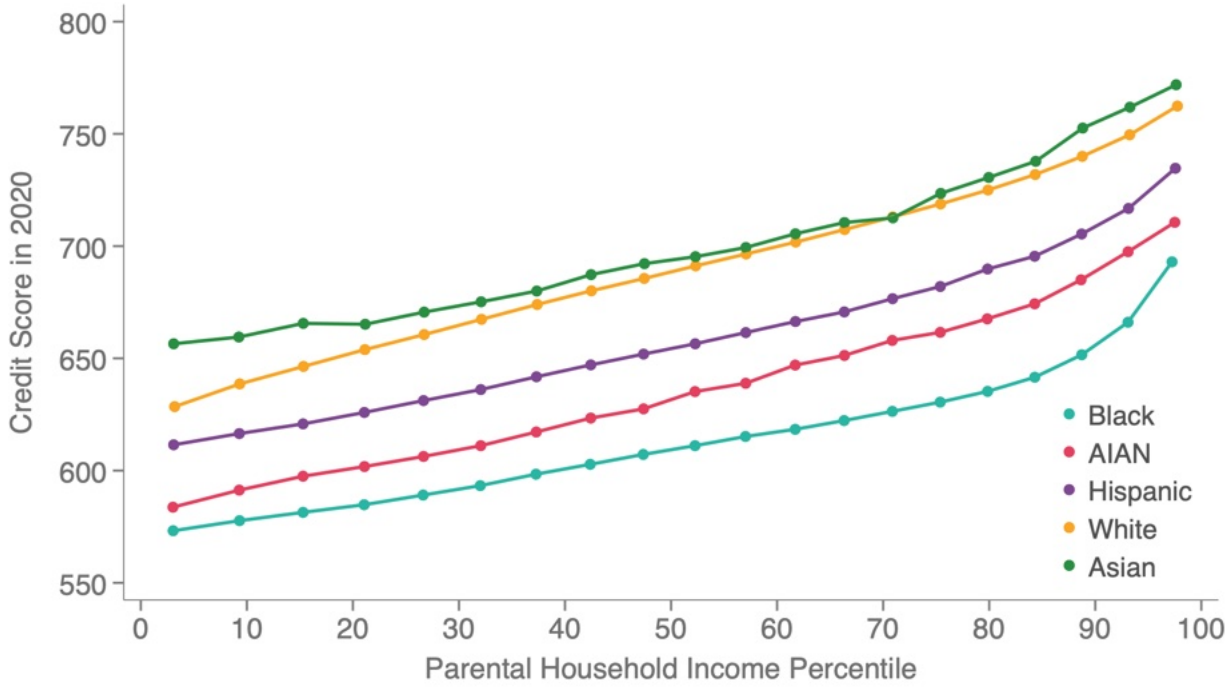


B. Parental Income Quintile



Notes: This figure presents the average number of tradelines by age, race, and parental income in 2020 in the population sample. Panel A reports the number of tradelines by age and race. Panel B reports the number of tradelines by age and parental income quintile, restricting to the birth cohorts we are able to match to parents.

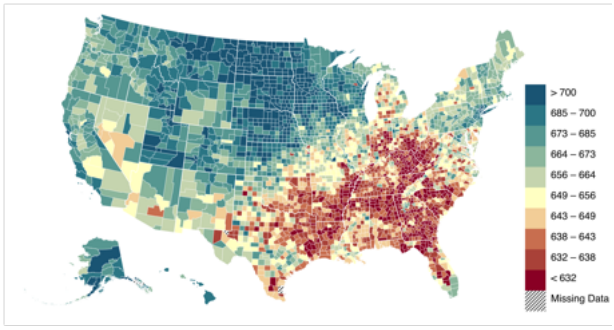
FIGURE A.3
Credit Scores by Race and Parental Income 2020, Children of Native-born Mothers



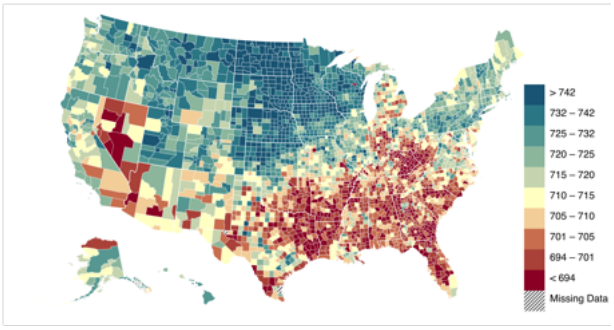
Notes: This figure presents the average credit scores in 2020 by race and parental income percentile as in Figure I Panel C, but restricts to the subset of children whose mothers were born in the US.

FIGURE A.4
Geography of Credit Scores by Race and Parental Income

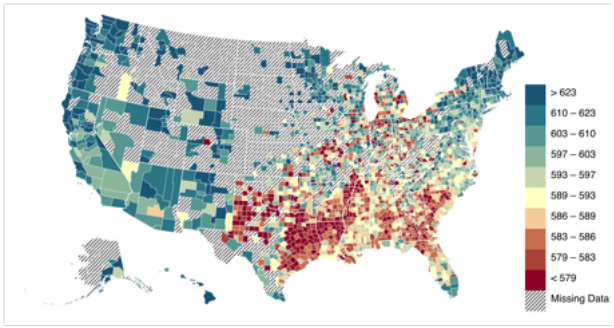
A. White, 25th Percentile Parental Income



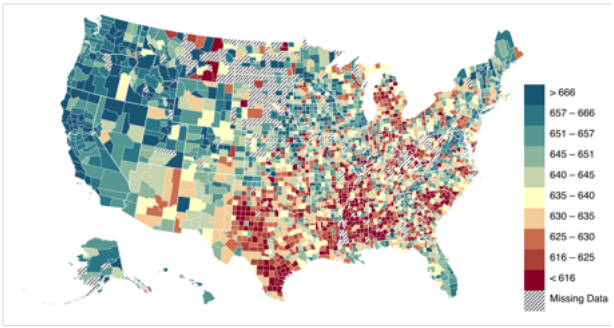
B. White, 75th Percentile Parental Income



C. Black, 25th Percentile Parental Income



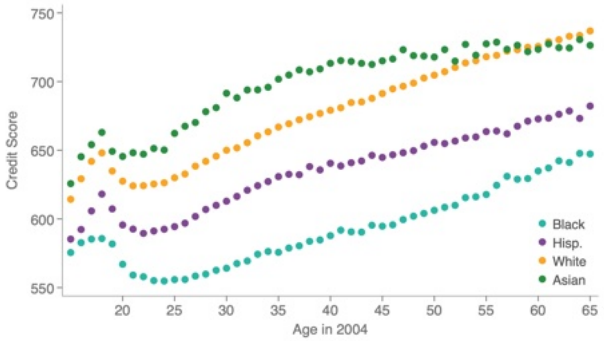
D. Hispanic, 25th Percentile Parental Income



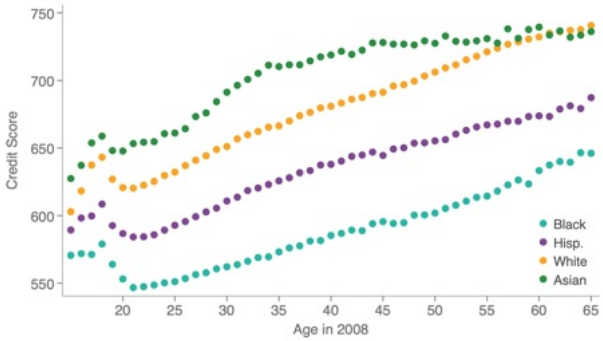
Notes: This map displays mean credit scores in 2020 for our intergenerational sample (born between 1978 and 1985) by the county in which they grew up. We first estimate the relationship between credit score and parental income rank using a lowess fit at the national level. For each county, we then regress individual credit scores on the transformed parental income rank (from the national lowess) to obtain the average credit score for individuals at different percentiles of the parental income distribution. Counties shown with black and white dashed lines are those with insufficient data. Panel A shows White individuals at the 25th percentile of the parental income distribution. Panel B shows White individuals at the 75th percentile of the parental income distribution. Panels C and D show the average credit scores for Black and Hispanic individuals, respectively, at the 25th percentile of the parental income distribution.

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

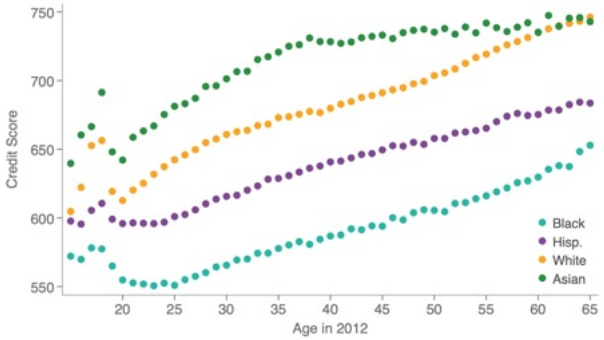
A. 2004



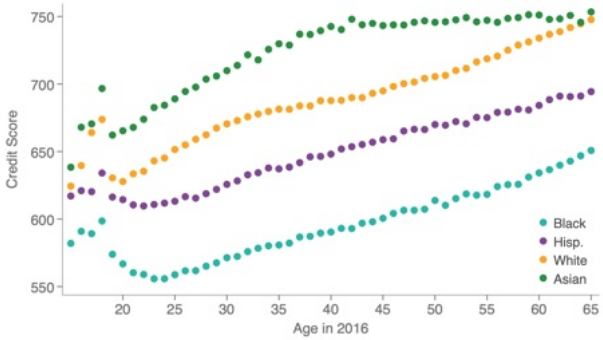
B. 2008



C. 2012



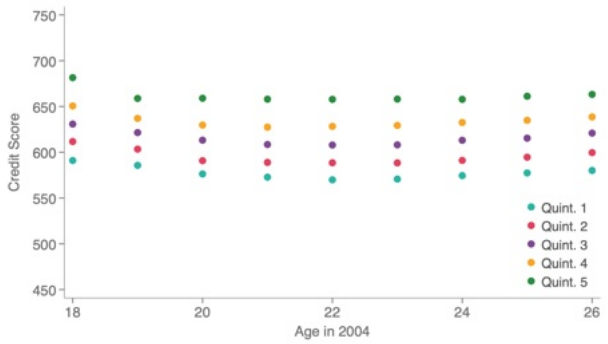
D. 2016



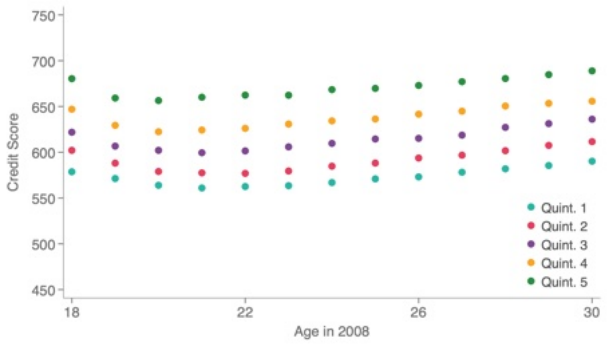
Notes: This figure presents the average credit score by age in years 2004, 2008, 2012, and 2016 by race in our population sample. White individuals have credit scores of 679, 681, 680, and 688 at age 40 in 2004, 2008, 2012, and 2016. Black individuals have credit scores of 588, 585, 587, and 590 at age 40 in 2004, 2008, 2012, and 2016.

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

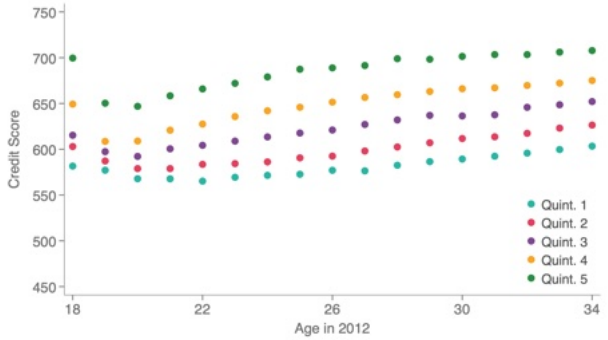
A. 2004



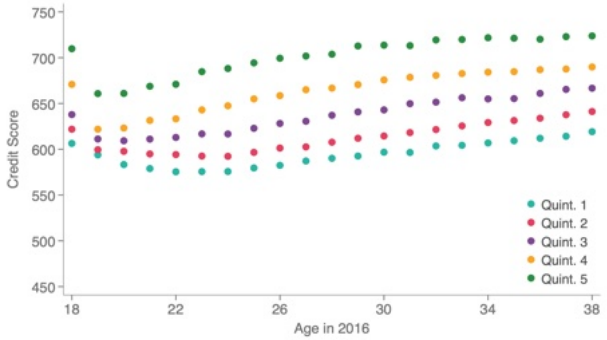
B. 2008



C. 2012

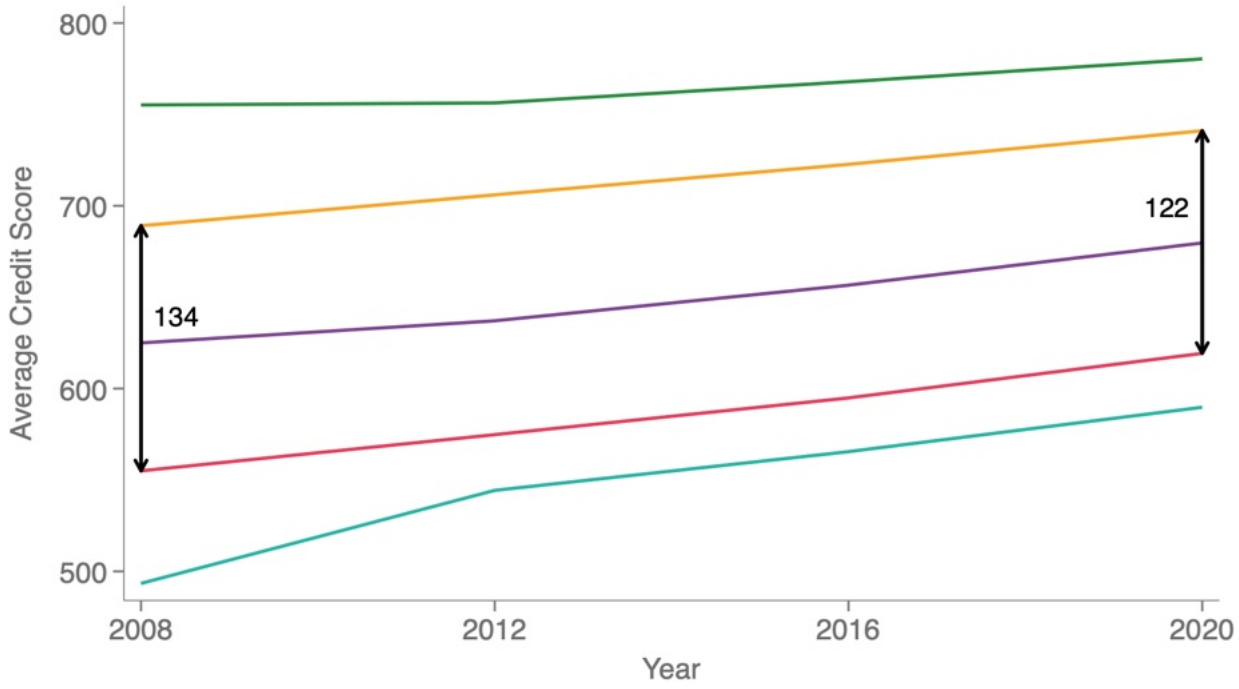


D. 2016



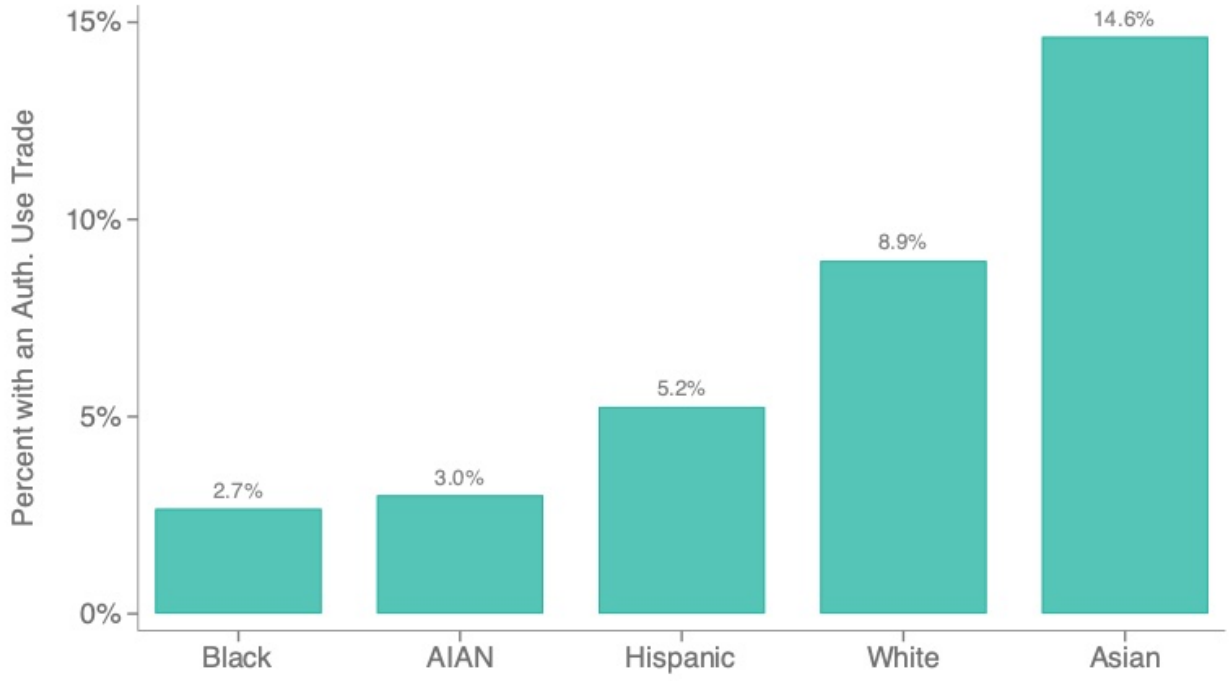
Notes: This figure presents the average credit score by age in years 2004, 2008, 2012, and 2016 by parental income quintile. People with parents in the top income quintile have credit scores of 689, 701, and 714 at age 30 in 2008, 2012, and 2016. People with parents in the bottom income quintile have credit scores of 590, 589, and 597 at age 30 in 2008, 2012, and 2016.

FIGURE A.7
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. The quantities on the plot are the score gaps in 2008 and 2020 between the averages of people in the second and fourth quintile of the credit score distribution in 2008.

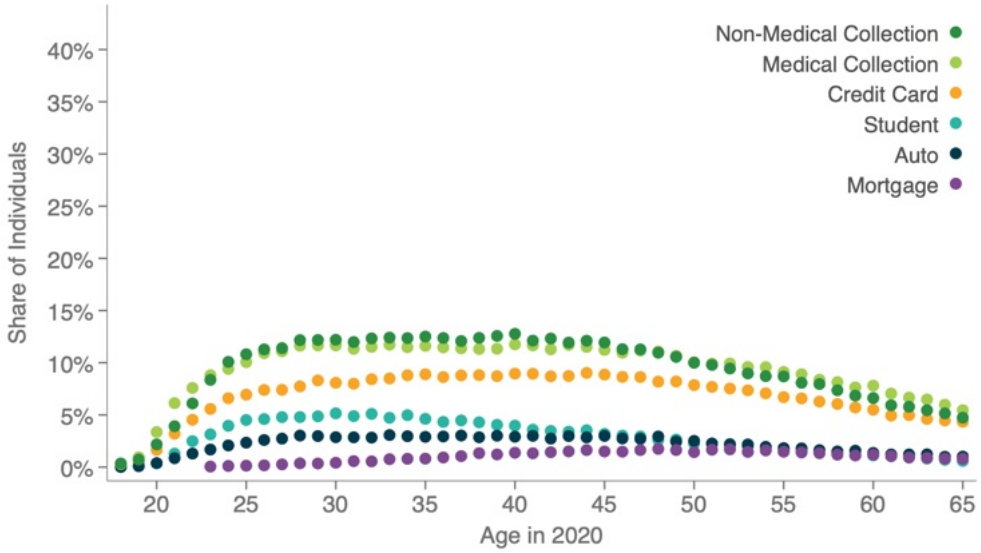
FIGURE A.8
Incidence of Authorized User Trades



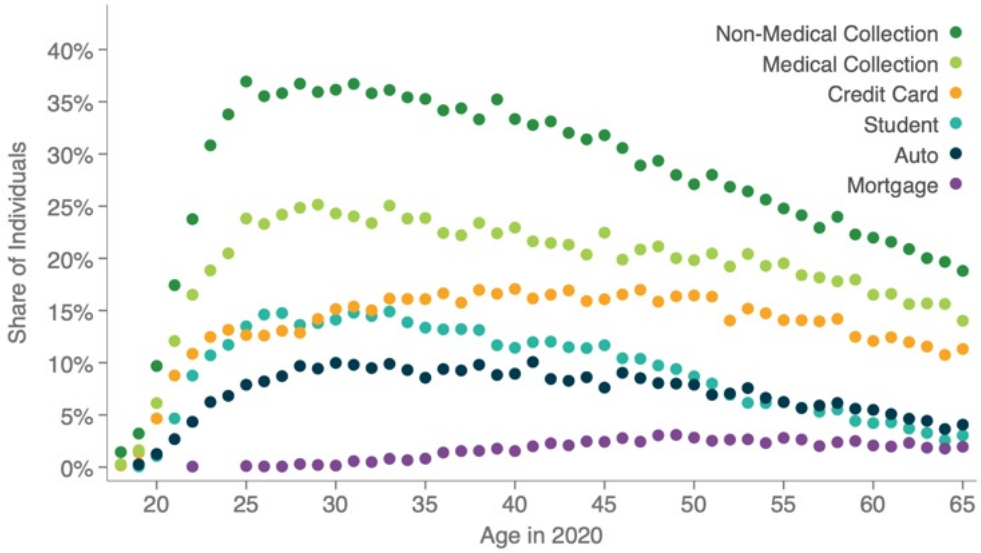
Notes: This figure presents percentage of individuals in our intergenerational sample (born between 1978 and 1985) in 2004 who have an authorized user trade, separately by race.

FIGURE A.9
Delinquency and Collection Type by Age

A. White

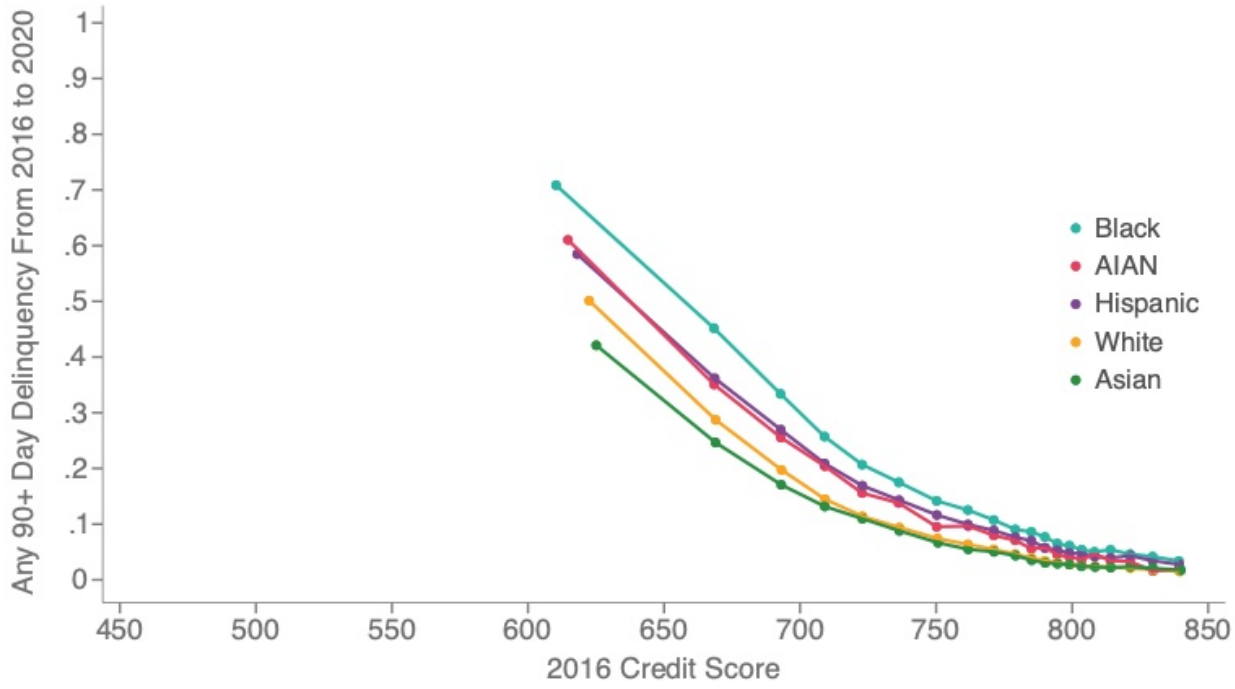


B. Black



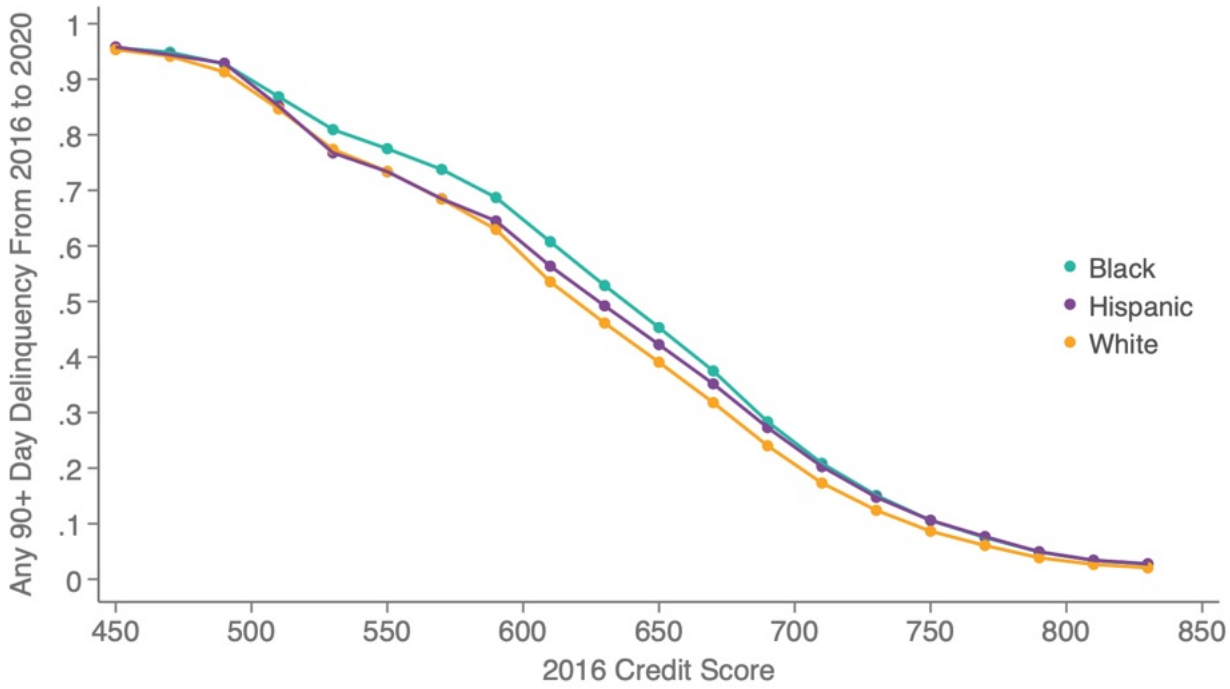
Notes: This figure shows the average rates of collections and 90+ day delinquencies on different tradelines for White individuals in Panel A and Black individuals in Panel B in 2020. Collections are split into non-medical and medical, and tradeline delinquencies are split by credit card, student loan, auto loan, and mortgages.

FIGURE A.10
90+ Day Delinquency versus Credit Score for those 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.

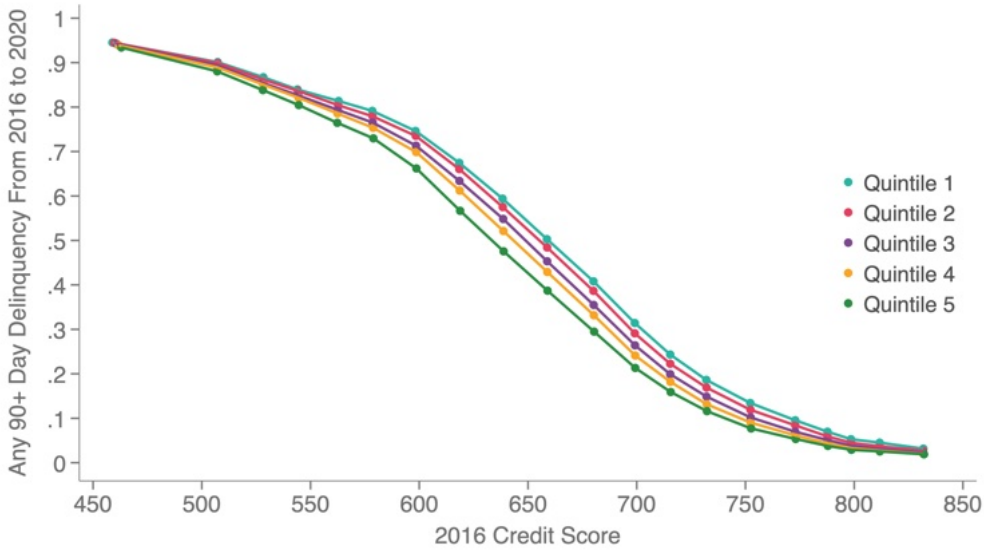
FIGURE A.11
90+ Day Delinquency versus Credit Score with Imputed Race, No Delinquencies



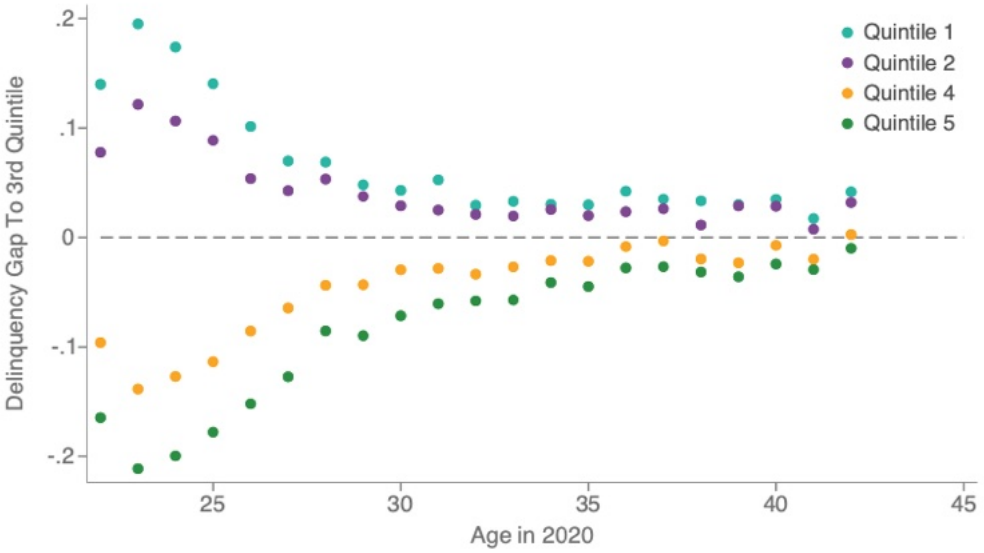
Notes: This figure presents the average 90+ day delinquency rate between 2016 and 2020 (using the 2020 credit file) as a function of the 2016 credit score on the horizontal axis, separately by race. We impute race as Black, Hispanic, or not-Black and not-Hispanic using the race shares of one's ZIP code. To most closely replicate the specification in VantageScore Solutions (2022), we restrict the sample to individuals without any 90+ day late payment on their credit report in 2016 (although this has only minor effects on the graph).

FIGURE A.12
Calibration Bias by Parental Income Quintile

A. Subsequent Non-Repayment Versus Credit Score

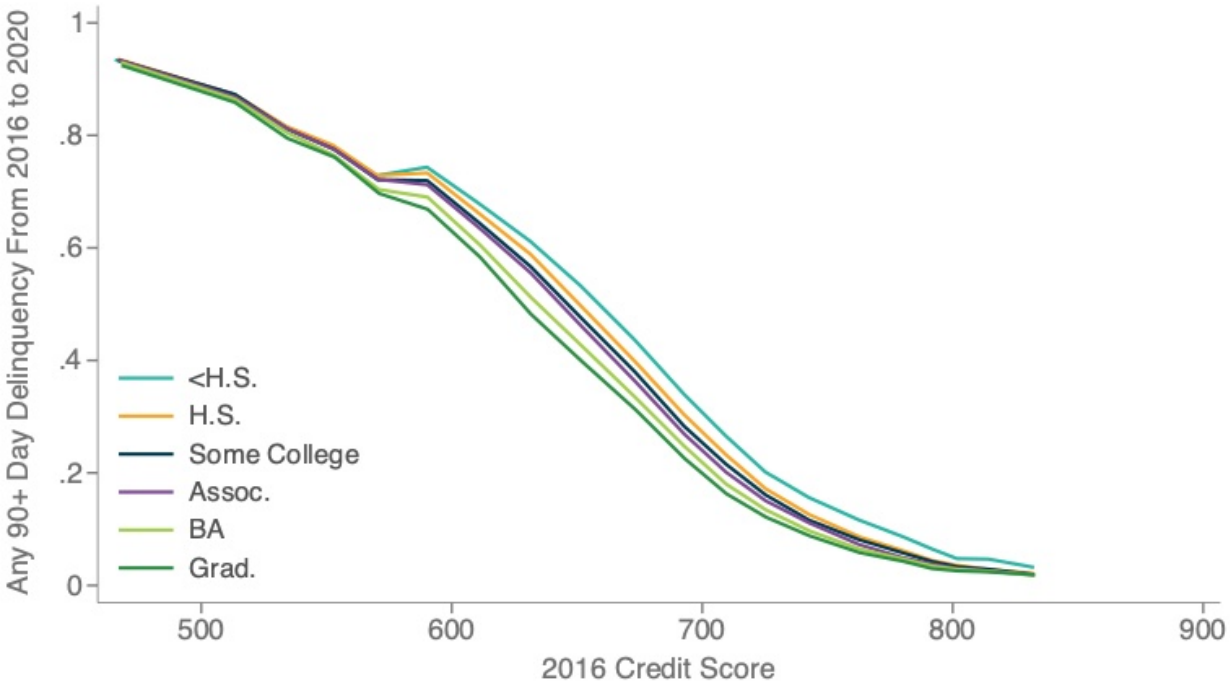


B. Bias by Age (Relative to Q3)



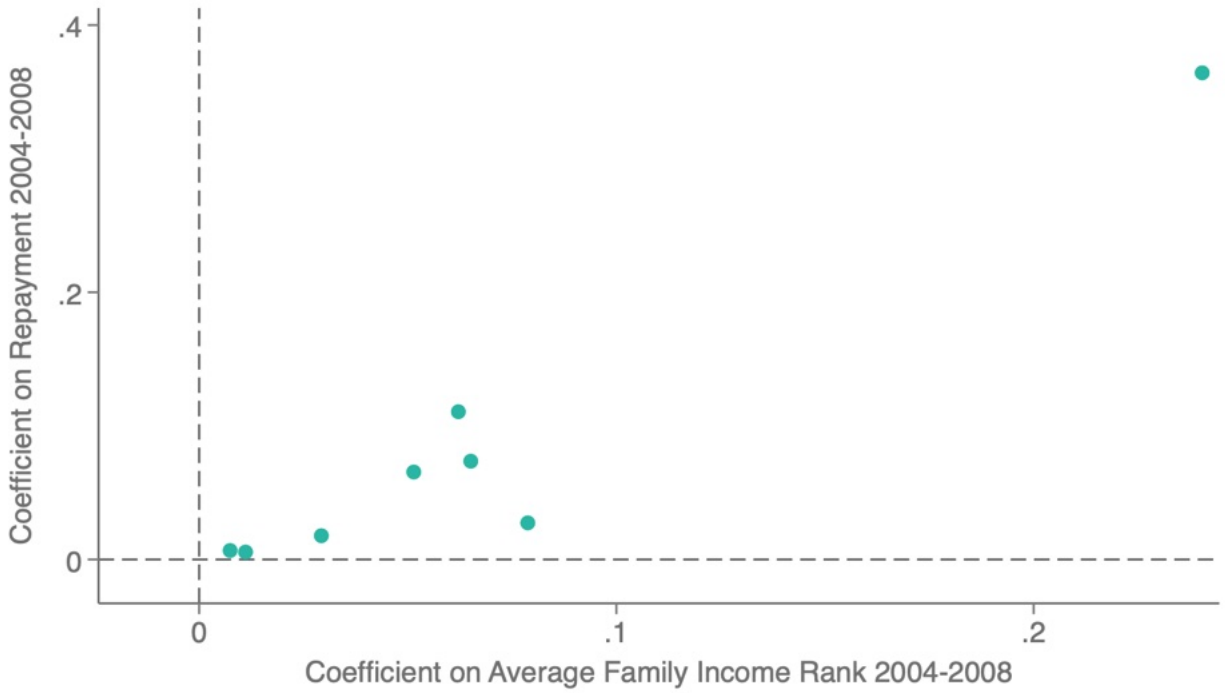
Notes: This figure presents the average 90+ day delinquency rate between 2016 and 2020 (using the 2020 credit file) as a function of the 2016 credit score on the horizontal axis, separately by parental income quintile. It uses the intergenerational sample (born between 1978 and 1985). In Panel B, this figure presents estimated coefficients from separate OLS regressions of 90+ day delinquency between 2016 and 2020 against 2016 credit scores and parental income quintile indicators for our population sample, where Quintile 3 is the omitted category, restricting to the birth cohorts we can match to parents. See Figure III for the same exercise using race.

FIGURE A.13
Calibration Bias by Parental Education



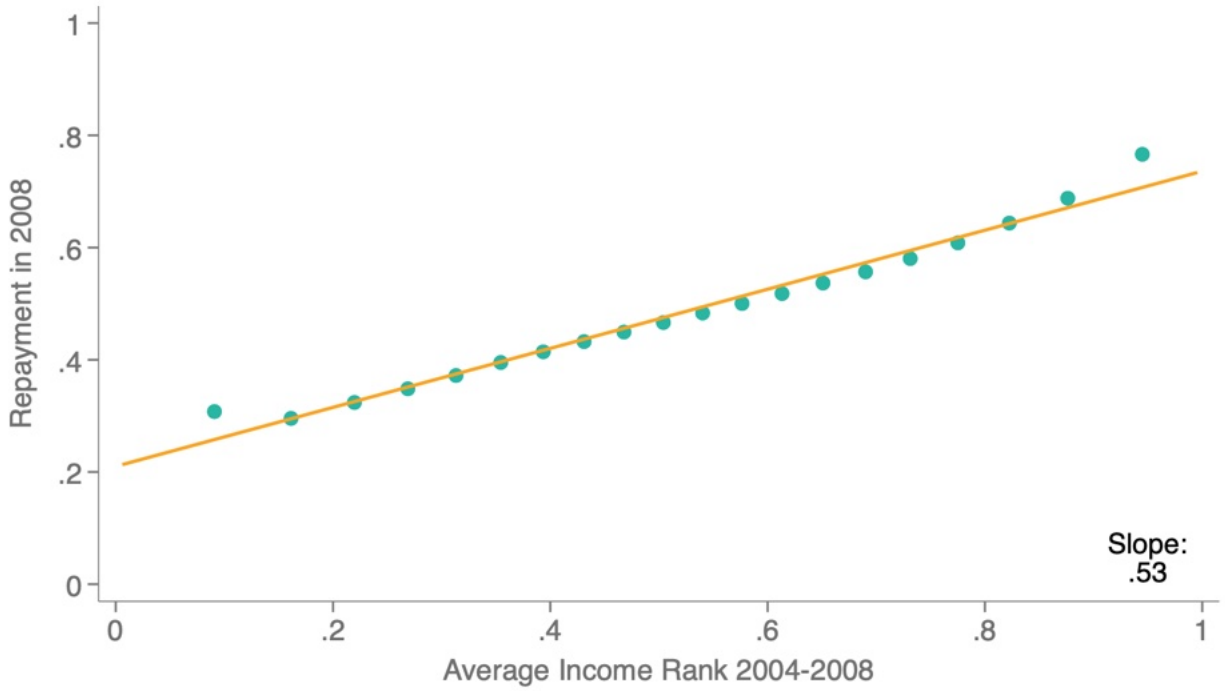
Notes: This figure presents the average 90+ day delinquency rate between 2016 and 2020 (using the 2020 credit file) as a function of the 2016 credit score on the horizontal axis, separately by parental education. It uses the intergenerational sample (born between 1978 and 1985).

FIGURE A.14
Correlation of Observables with Income and Repayment



Notes: This figure presents a scatter plot of the coefficients from multivariate regressions of income and repayment on a vector of covariates, X_i, that include the following variables: home-ownership, education (high school), mom's education (high school and college), healthcare coverage, family income level and rank in 2020, and marital status in 2020. The coefficients with repayment (defined as no instances of a 90+ day delinquency from 2004-2008), β_{1k}, are on the y-axis. The coefficients with average household income rank from 2004-2008 as the outcome, β_{2k}, are on the x-axis.

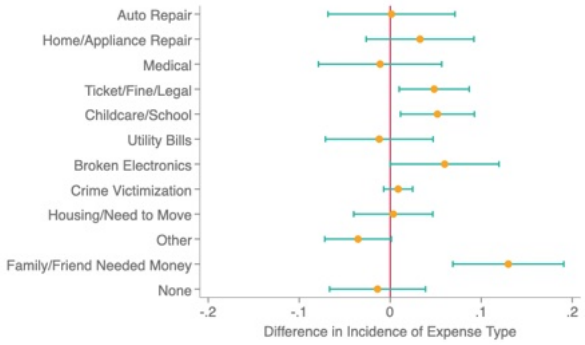
FIGURE A.15
Binscatter of Repayment versus Income



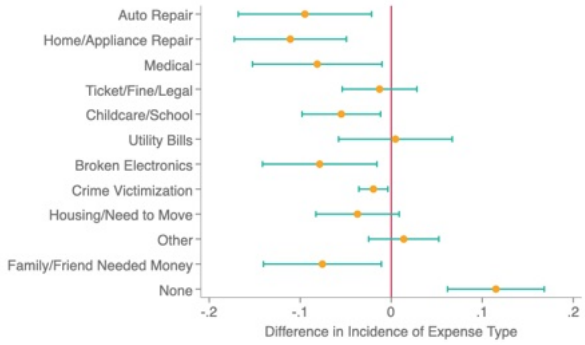
Notes: This figure presents a binned scatter plot of repayment (no 90+ day delinquency between 2004 and 2008) against the average family income rank between 2004 and 2008, using our intergenerational sample. Figure IV Panel A depicts the same relationship when also including controls for race, parental income, and hometown.

FIGURE A.16
Incidence of Types of Unexpected Expenses by Group (Prolific)

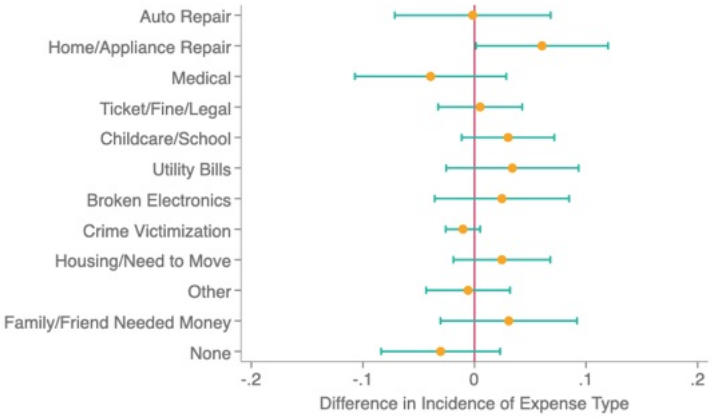
A. Black vs White



B. Low vs. High Parental Education

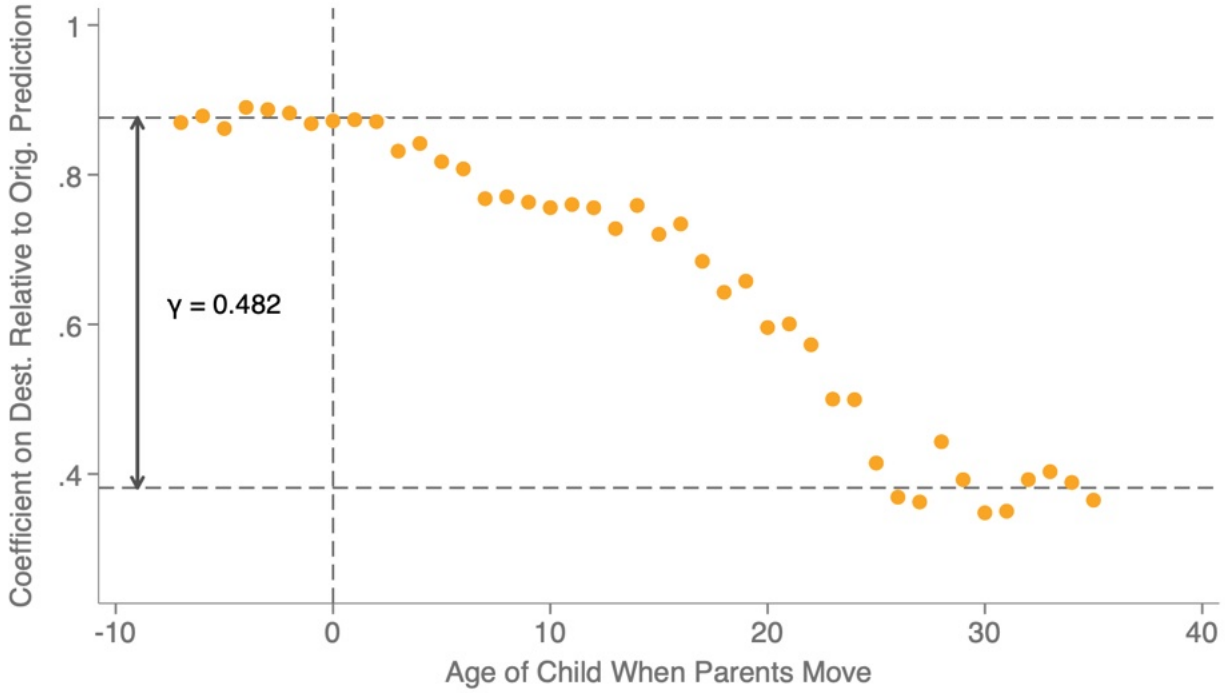


C. Low vs. High County-Level Repayment



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 asked of our 702 Prolific survey respondents aged 22-30: 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. 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.17
Childhood Exposure Effects Controlling for Income in Adulthood



Notes: This figure presents estimates of the coefficients β_m plotted against the child's age when the parents move (m_i) using the specification in Equation 12 in our intergenerational sample (born between 1978 and 1985), adding a term for average family income rank between 2004 and 2008. The outcome variable is an indicator for whether a child had a 90+ day delinquency between 2004 and 2008. The figure reports an estimate of the fraction of the hometown gap that is explained by childhood exposure, γ, where we regress β_m on the spline from Equation 13.

TABLE A.1
Balance Bias

	1978-85 Cohorts	No 90+ Day Delinquencies	90+ Day Delinquencies	Never Late
	(1)	(2)	(3)	(4)
White score	681	735	591	551
Black gap	103	75	39	16
Asian gap	-40	-17	-26	-10
Hispanic gap	46	36	9	0
High par. income score	694	741	599	554
Low par. income gap	70	41	30	12
Low delinq. hometown score	679	732	589	550
High delinq. hometown gap	37	14	16	7

Notes: This table evaluates the presence of balance bias by race, parental income, and hometown in our intergenerational sample using credit scores from 2016 and 90+ day delinquency between 2016 and 2020. Column 1 reports the average credit score and gaps among all individuals. Column 2 restricts to individuals that do not experience a 90+ day delinquency between 2016 and 2020. Column 3 restricts to individuals that experience a 90+ day delinquency between 2016 and 2020. Column 4 restricts to individuals that experience no 30+ day delinquency from 1997-2020, the full scope of our data.

TABLE A.2
Estimation of Median Credit Scores by Race/Ethnicity

	True Median	Zipcode Weighted By Population	Median Credit Score Mortgage Holders
Race	(1)	(2)	(3)
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 in Column 1 ("True Median") from our population sample with estimates of the median credit score by race using ZIP codes where more than 60% of the population identifies as a given racial group in Column 2 ("Zip Code Weighted By Population"). 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 second column. Column 3 ("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.3
Mean Credit Scores by Race/Class and Sex in 2020

	Intergenerational Sample		Population Sample	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
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 A.4
Collections by Race and Parental Income

		Race				Parental Income			
	All	White	Black	Asian	Hisp.	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:									
Fraction with Collections									
Overall	0.332	0.277	0.626	0.116	0.403	0.541	0.430	0.285	0.141
Medical	0.197	0.179	0.361	0.058	0.216	0.321	0.263	0.173	0.085
Nonmedical	0.234	0.177	0.489	0.083	0.300	0.391	0.303	0.197	0.088
Utilities	0.153	0.113	0.347	0.050	0.186	0.274	0.199	0.118	0.053
Retail	0.056	0.042	0.107	0.021	0.087	0.092	0.072	0.051	0.021
Student Loan	0.006	0.004	0.015		0.006	0.009	0.008	0.006	0.003
BFCU	0.084	0.067	0.156	0.033	0.114	0.126	0.111	0.080	0.034
Panel B:									
Average Collection Amount									
Overall	2,882	2,776	3,106	2,687	2,862	3,062	2,859	2,790	2,378
Medical	2,463	2,473	2,505	2,468	2,373	2,799	2,394	2,235	1,821
Nonmedical	2,018	1,833	2,131	2,048	2,130	1,937	1,985	2,073	2,048
Utilities	879	787	984	885	866	901	907	836	703
Retail	1,140	1,182	927	1,274	1,255	1,078	1,060	1,109	1,360
Student Loan	3,357	2,915	4,022		1,545	3,325	3,040	3,711	2,599
BFCU	1,844	1,724	1,722	1,937	2,080	1,655	1,769	1,974	2,041

Notes: In Panel A, this table reports the fraction of our population sample that has collections at age 30. Fractions are reported for all collections, then broken into medical versus nonmedical collections. Nonmedical collections are broken into utility, retail, student loan, and banking, financial, and credit union collections. In Columns 2–5, fractions are reported for White, Black, Asian, and Hispanic individuals. In Columns 6–9, fractions are reported for individuals with parents in the first, second, third, and fourth quartile of the income distribution. In Panel B, this table reports average collection balance among those who have a positive collection amount with each collection type. Missing cells are suppressed due to sample sizes being below the 10 count threshold in accordance with Census Bureau disclosure policies.

TABLE A.5
Oaxaca-Blinder Decomposition of Repayment Gaps by Income

	Gap	White, High Par. Income α			Other Group α		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
White-Black	0.37	17%	20%	21%	8%	15%	17%
White-Asian	-0.13	-14%	-5%	0.00	-5%	5%	9%
White-Hispanic	0.19	10%	17%	19%	7%	13%	15%
High-low par. income	0.28	11%	17%	19%	12%	18%	20%
Income		Average	Quartiles	Deciles	Average	Quartiles	Deciles

Notes: This table presents the estimates of the percent of repayment gaps that can be explained by income in our intergenerational sample (born between 1978 and 1985) in 2008. It is estimated analogously to Table IV, except values of $\boldsymbol{\alpha}$ are calculated using within-group values. Column 1 reports the repayment gap. Columns 2–4 report the estimates using White or high parental income $\boldsymbol{\alpha}$s. Columns 5–7 report the estimates using Black, Asian, Hispanic, or low parental income $\boldsymbol{\alpha}$s. Columns 2 and 5 define income as the average household income rank between 2004-2008. Columns 3 and 6 define income as an interaction dummy of family income rank quartile in each year between 2004 and 2008. Columns 4 and 7 define income as an interaction dummy of family income rank decile in each year between 2004 and 2008.

TABLE A.6
Decomposition of Repayment Gaps using 2004-2020 Income Vector

	Repayment in 2004-2008		Repayment in 2016-2020	
	Gap	Explained	Gap	Explained
	(1)	(2)	(3)	(4)
White-Black	0.37	32%	0.38	36%
White-Asian	-0.13	21%	-0.14	31%
White-Hispanic	0.19	30%	0.17	40%
High-low par. income	0.27	35%	0.25	45%
Hometown variance	0.01	12%	0.02	13%
N	26,000,000	26,000,000	25,910,000	25,910,000
AUC		0.74		0.77

Notes: This table presents the estimates of the percent of repayment gaps in young adulthood (2004-2008, Column 1) and mid-life (2016-2020, Column 3) that can be explained by the full vector of income from 2004 to 2020 in our intergenerational sample (born between 1978 and 1985). It is estimated analogously to Table IV. Column 2 decomposes gaps in repayment between 2004 and 2008, and Column 4 decomposes gaps in repayment between 2016 and 2020. The AUC row is the area under the receiver operating characteristic (ROC) curve from the repayment predictions generated by a linear model of the full vector of present and future income (without race, class, or hometown). As a point of reference, the AUC for race, class, and hometown is 0.723.

TABLE A.7
Decomposition of Conditional Repayment Gaps by Income 2008

	Intergenerational Sample					SIPP Sample		SIPP Alone or Married Sample	
	Gap	Explained				Gap	Exp.	Gap	Exp.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Par. Income									
White-Black	0.31	11%	12%	10%	-8%	0.31	28%	0.31	29%
White-Asian	-0.09	-20%	-15%	-3%	-17%	-0.08	36%	-0.21	2%
White-Hispanic	0.16	8%	9%	17%	22%	0.18	17%	0.16	24%
Hometown variance	0.07	2%	3%	12%	72%	0.08	12%	0.11	13%
Panel B: Credit Score									
White-Black	0.21	10%	12%	6%	-29%	0.18	42%	0.13	22%
White-Asian	0.01	400%	432%	323%	484%	0.04	10%	-0.04	-149%
White-Hispanic	0.14	7%	10%	19%	19%	0.13	39%	0.15	21%
High-low par. income	0.24	7%	10%	11%	18%	0.25	48%	0.20	32%
Hometown variance	0.07	2%	3%	13%	79%	0.08	11%	0.11	12%
N	26 M	26 M	26 M	26 M	26 M	7,200	7,200	1,900	1,900
AUC		0.64	0.68	0.61	0.61		0.75		0.75
Inc 04-08 control		Average	Vector	Quartiles	Deciles		Vector		Vector
Wealth controls							X		X

Notes: This table presents the estimates of the percent of repayment gaps conditional on parental income and credit score that can be explained by income and wealth in our intergenerational sample (born between 1978 and 1985) in 2008. It is estimated analogously to Table IV, except it is reweighted so that the distribution of parental incomes (Panel A) or credit scores (Panel B) within each subgroup matches the national distribution of parental incomes or credit scores, as described in Appendix G. Column 1 reports the repayment gap in the intergenerational sample (born 1978-1985) after reweighting. Column 2 defines income as the average family income rank from 2004-2008. Column 3 defines income as a vector of family income ranks from 2004-2008. Column 4 uses a nonparametric control for the sequence of income quartiles between 2004 and 2008. Column 5 uses a nonparametric control for the sequence of income deciles between 2004 and 2008. Columns 6 and 8 report the repayment gap among SIPP matched individuals in 2003 and 2004. Columns 7 and 9 use the vector of incomes and include wealth controls for liquid assets and net wealth. Columns 6 and 7 use all individuals matched to the SIPP, while Column 8 and 9 restrict to individuals living alone or with a married spouse. The AUC row is the area under the receiver operating characteristic (ROC) curve from the repayment predictions generated by a linear model of income and wealth after reweighting so the parental income and credit score distributions match between groups (without race, class, or hometown). As a point of reference, the AUC for race, class, and hometown is 0.723.

TABLE A.8
Repayment Gaps Conditional on Parent Credit Score

Panel A: Decomposition	(1)	(2)
White-Black	0.38	37%
White-Asian	-0.13	16%
White-Hispanic	0.19	38%
High-low parent income	0.26	47%
N	4,152,000	4,152,000

Panel B: Regression	(1)	(2)	(3)	(4)	(5)	(6)
Par. Credit Score in 2004 (100)	-0.200***	-0.196***	-0.161***	-0.152***	-0.144***	-0.130***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.028)
Income Rank in 2004		-0.144***	-0.135***	-0.100***	-0.124***	0.032
		(0.001)	(0.001)	(0.001)	(0.002)	(0.078)
Parent Income Rank			-0.244***	-0.214***	-0.142***	-0.126
			(0.001)	(0.001)	(0.002)	(0.107)
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

Notes: In Panel A, this table reports the estimates of the percent of repayment gaps that can be explained by parental credit score in our intergenerational sample (born between 1978 and 1985) in 2008. It is estimated analogously to Table IV, except rather than use income or wealth, we calculate $\boldsymbol{\alpha}$s to predict repayment gaps based on parental credit score. In Panel B, this table presents estimated coefficients from an OLS regression of any 90+ day delinquency from 2004 to 2008 against parental credit score in 2004 divided by 100. Column 1 reports a univariate regression of delinquency on parental credit score. 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 parental 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 A.9
Financial Literacy by Group (Prolific Survey)

	Financial Literacy Measure				
	Credit Report Duration	Correct Duration	Know Credit Score	Missed Payment	
	(1)	(2)	(3)	(4)	(5)
Black	-0.959***	-0.104**	-0.027	0.136***	0.136***
	(0.252)	(0.041)	(0.033)	(0.044)	(0.044)
Parent Education	-0.069	-0.013	-0.008	-0.013	-0.013
	(0.049)	(0.008)	(0.006)	(0.008)	(0.008)
Chldhd Cnty Repayment Rate	2.915**	0.381	0.337*	-0.517**	-0.514**
	(1.421)	(0.233)	(0.188)	(0.248)	(0.249)
Credit Report Duration					-0.015
					(0.010)
Correct Duration					0.147**
					(0.059)
Know Credit Score					-0.047
					(0.057)
Education Controls	X	X	X	X	X
N	551	551	551	551	551
R^2	0.100	0.055	0.012	0.036	0.047

Notes: This table examines group differences in understanding about credit reports and assesses whether those differences help explain differences in repayment using data from our Prolific sample of US 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. Column 2 repeats the regression with the dependent variable equal to 1 if the respondent gave the correct answer ("7 years") and 0 otherwise. Column 3 repeats the regression with the dependent variable equal to 1 if the respondent knows their own credit score and 0 otherwise. Column 4 regresses a missed-payment indicator on the same group variables and education controls. Column 5 adds the three literacy measures from Columns 1—3 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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

TABLE A.10
Informal Transfers Incidence by Group (Prolific Survey)

	Informal Transfers Incidence						
	Gave Fncl Assist (1,000s)	Gave Fncl Assist (Freq)	Times Asked for Help	Amount Could Borrow (1,000s)	Missed Payment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	0.137	0.774***	1.617***	-0.464***	0.111***	0.081**	0.024
	(0.112)	(0.143)	(0.255)	(0.160)	(0.040)	(0.039)	(0.039)
Parent Education	0.030	0.036	0.044	0.158***	-0.014*	-0.008	-0.010
	(0.021)	(0.027)	(0.048)	(0.030)	(0.007)	(0.007)	(0.007)
Chldhd Cnty Repayment Rate	-1.315**	-3.384***	-5.039***	0.881	-0.449**	-0.342	-0.187
	(0.615)	(0.788)	(1.402)	(0.882)	(0.218)	(0.215)	(0.209)
Gave Fncl Assist (1,000s)						0.047***	0.018
						(0.014)	(0.014)
Amount Could Borrow						-0.051***	-0.043***
						(0.010)	(0.009)
Times Asked for Help							0.040***
							(0.006)
Education Controls	X	X	X	X	X	X	X
N	702	702	702	702	702	702	702
R^2	0.033	0.130	0.122	0.074	0.027	0.070	0.127

Notes: This table reports OLS regression estimates from our Prolific survey of 702 US adults aged 22-30 that relate demographic factors to incidence of informal transfers. Each 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). 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. Columns 5–7 use an indicator that equals 1 if the respondent missed any loan or bill payment in the past 12 months as the dependent variable. Column 5 includes the baseline covariates. Column 6 adds controls for the annual dollar amount (in $1,000s) given to others and the dollar amount (in $1,000s) the respondent felt they could borrow from individuals in their network. Column 7 additionally controls for the number of times the respondent was asked for financial help in the past three years. All estimates use conventional (non-robust) standard errors, shown in parentheses. We also report p-value thresholds: *** p < 0.01, ** p < 0.05, * p < 0.10.

B Conceptual Framework

Why would lenders use the credit score to set the terms of one's access to credit? Here, we provide a simple model of competitive lending to individuals with different credit histories and likelihood of future delinquencies that shows how the credit score can be useful for a lender when considering the terms to offer for additional credit. Consider an economy populated by a set of individuals indexed by i who hold a status quo amount of debt b_i, and have a credit history, h_i, that contains information on their balances, past delinquencies, and types of accounts. Let d_i denote the event that the individual falls delinquent in the future on this debt. The credit score, s, aims to predict this future delinquency using the credit history $s(h_i) = f(E[d_i|h_i])$, where f is a 1-1 transformation of this prediction (i.e. for some reason, credit bureaus prefer to report a credit score on a range from 300 to 850 instead of [0,1]).

There exists a set of risk-neutral lenders that compete to offer a loan of size \$1 to individuals. They offer interest rates, $R(s)$, that are conditional on the credit score. Each individual observes the interest rate and decides whether to take the additional loan. We assume symmetric information so that borrowers have no more information about future delinquency conditional on the credit score. Under two assumptions, the credit score captures the delinquency risk faced by marginal lenders. First, we assume that individuals default on the additional \$1 loan if and only if they fall delinquent on their existing stock of debt. Second, in general we would expect the additional loan to affect the probability of future delinquency. However, for a loan that is small relative to the stock of debt, this effect is second order. Hence, one can assume that the marginal loan is sufficiently small in size so that it does not affect this probability of delinquency. Under these two assumptions, $E[d_i|h_i]$ captures the expected delinquency for a new \$1 loan.

We assume the lending market is perfectly competitive and that lenders face a gross cost of capital, $\rho > 1$. We assume that lenders receive $R(s(h_i))$ in the event the borrower does not fall delinquent but only recovers a fraction, f, of the amount due. In expectation, they receive $R(s(h_i))(1-(1-f)E[d_i|h_i])$. The zero profit condition implies that lenders set interest rates that satisfy

$$R(s(h_i)) = \frac{\rho}{1-(1-f)E[d_i|h_i]}. \tag{B.16}$$

For example, individuals who have a 50% likelihood of delinquency and lenders recover 50% in the event of delinquency, they will face a gross cost of borrowing that is 33% higher than the lenders cost of capital. If ρ is 1.05 (5% interest rate), then such borrowers will face $R = 1.05 * 4/3 = 1.40$, or a 40% interest rate.

In this sense, the credit score (i.e. prediction of future delinquency) is useful for a lender considering the provision of additional credit to a borrower, as it helps forecast the profitability of the marginal loan.

C Algorithmic Bias

In this appendix, we provide greater detail on our findings on the presence of algorithmic bias in credit scores. We discuss two forms of bias: calibration bias and balance bias.

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:

$$\Pr\{Y = 1|S = s, R = Black\} = \Pr\{Y = 1|S = s, R = White\}. \tag{C.17}$$

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, 2026; Huang, Mayer and Miller, 2024; Arnold, Dobbie and Yang, 2018; Dobbie et al., 2021; Canay, Mogstad and Mountjoy, 2024).[63]

One way to think about our measure of calibration bias is that, under two assumptions, it studies 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.[64] 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.[65] 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 III Panel A in the main text provides evidence of calibration bias by race in our data. We find that Black individuals have consistently higher delinquency rates than White and Asian individuals with

[63] 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.

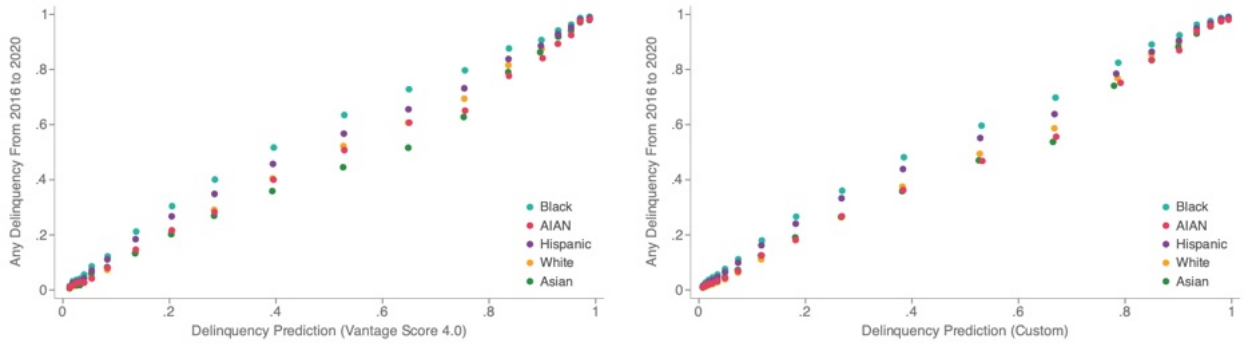
[64] Our inability to observe delinquencies on loans that aren't offered is analogous to other settings where outcomes are only observed under certain decisions. For example, judges are supposed to make bail decisions based on defendants' potential pre-trial misconduct, which cannot be observed if they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

[65] Closely related, Blattner and Nelson (2024) 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.

the same credit score. Hispanic and AIAN individuals' delinquency rates fall between Black and White individuals. These 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.18 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.

FIGURE A.18
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 versus a simple logit regression using a vector of credit score attributes. The attributes include the VantageScore 4.0 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 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.

Balance Bias Another measure of bias measures equal-odds or *balance* bias (Berk et al., 2017; Zafar et al., 2017; Bohren, Hull and Imas, 2025; 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

$$E[S|Y = y, R = Black] = E[S|Y = y, R = White], \tag{C.18}$$

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.[66]

To assess potential balance bias in credit scores, we compare the average 2016 credit scores between individuals with no 90+ day delinquencies ($Y = 0$) from 2016 to 2020 in each racial group in Appendix Table A.1 Column 2. This sample of Black individuals are assigned credit scores that are 75 points lower, and Hispanic individuals are assigned credit scores that are 36 points lower than White individuals. In contrast, Asian individuals are assigned scores 17 points higher than White individuals. Column 3 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 39 points higher than Black individuals and 9 points higher than Hispanic individuals.

We find similar patterns when analyzing balance bias by class. Appendix Table A.1 Column 2 also shows that those from the bottom quintile who have no 90+ day delinquencies between 2016-2020 are assigned credit scores in 2016 that are 41 points lower than those from the top quintile of the parental income distribution. Column 3 reports that among delinquent individuals, those from bottom quintile families received credit scores that are 30 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 on these other dimensions.

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. Appendix Table A.1 reports the average 2016 credit scores among individuals with no recorded delinquencies between 1997 and 2020—a window that spans 19 years before and four years after credit score assignment.[67] Within this set of "perfect repayment" individuals, we continue to find significant, albeit attenuated, differences in credit scores by race and class. Black individuals in our intergenerational sample have an average credit score of 535, in contrast to 551 for White individuals, 561 for Asian, and 551 for Hispanic individuals. 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

[66] 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 63, we leave the study of the causal effect of the score as an important direction for future work.

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

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 affirms our finding that differences in delinquency rates are the primary driver of the large gaps in credit scores that we observe by one's background.

D Data Appendix

D.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.

D.B Measurement of Hometown Variation

We follow the strategy of Chetty et al. (2026*a*) to measure the variation in credit scores by hometown 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. 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. For children who moved during 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.

D.C 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.[68] 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 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).

D.D Prolific Survey

We administered a bespoke online instrument through Prolific Academic, a large opt-in research panel that recruits US 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%

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

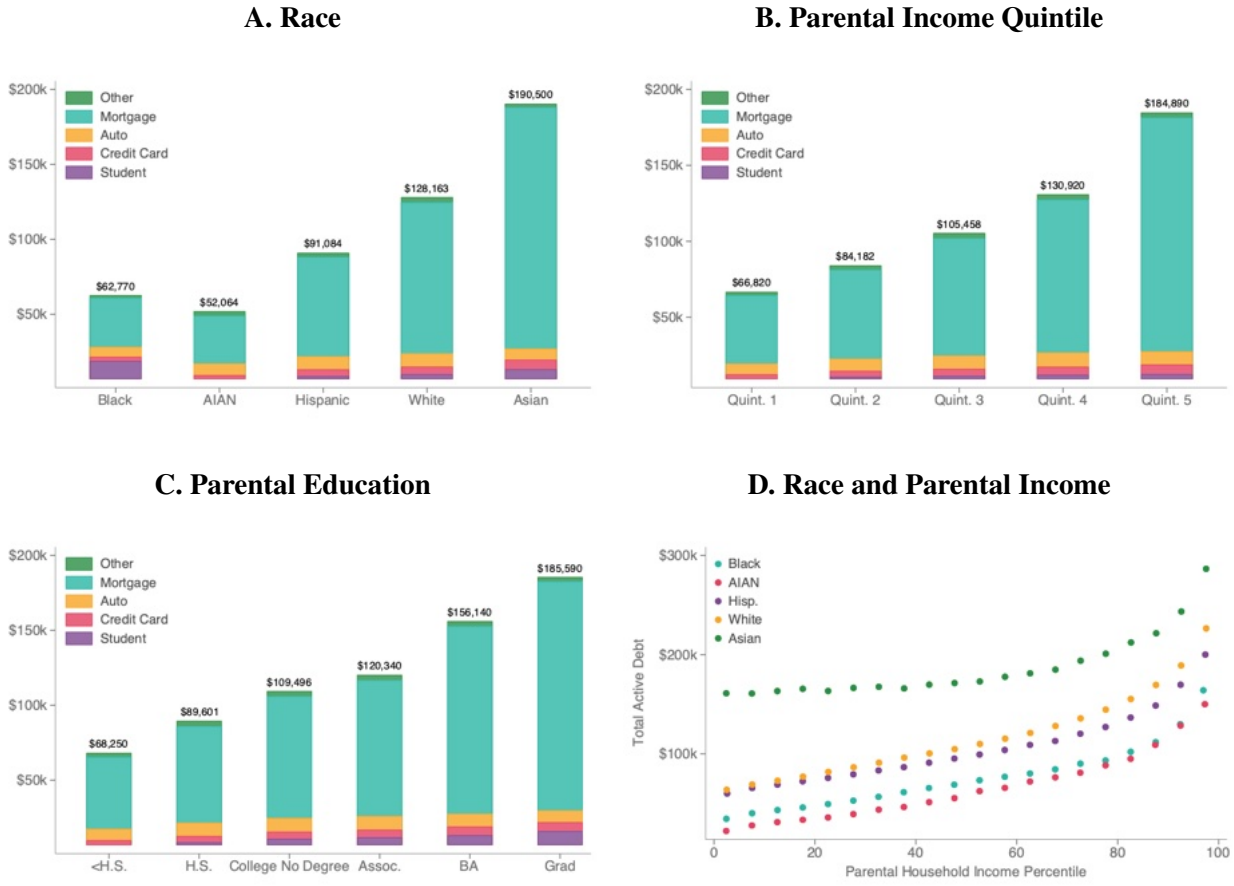
report at least one parent with a bachelor's degree, 48% hold a college degree themselves, and self-reported mean annual income is $74,457 among Black participants and $65,713 among White participants. After list-wise deletion for item non-response, the analytic sample used in Appendix Figure A.16 and Appendix Tables A.10, A.15, and A.17 comprise 702 individuals. Less respondents answer the credit duration knowledge question, so the analytic sample in Appendix Table A.9 comprises 551 individuals.

The survey contains five modules. 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 reported being behind on a bill or loan. These self-reported delinquency measures are slightly lower than the credit bureau data, though qualitatively similar.[69]

The other four modules include: (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 A.17). (iii) Financial networks (frequencies and dollar amounts of transfers to and from friends or family, the maximum amount respondents believe they could borrow informally) and unexpected expense categories (Appendix Figure A.16). (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.

[69] 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.

FIGURE A.19
Composition of Total Debt in 2020



Notes: This figure presents the average total debt and the composition of debt by subgroup in the intergenerational sample (born between 1978 and 1985) in 2020. In Panels A, B, and C, it presents a stacked bar chart of average debt holdings by 4 types of credit: mortgages, auto loans, credit card balances, and student loans, which comprise nearly all debt on credit reports. We also present a fifth "other" category. Panel A reports average debt by race, Panel B reports average debt by parental income quintile, and Panel C reports average debt by parental education. Panel D presents a binned scatter plot of total active debt on parental income percentile by race.

E 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. Appendix Figure A.19 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.

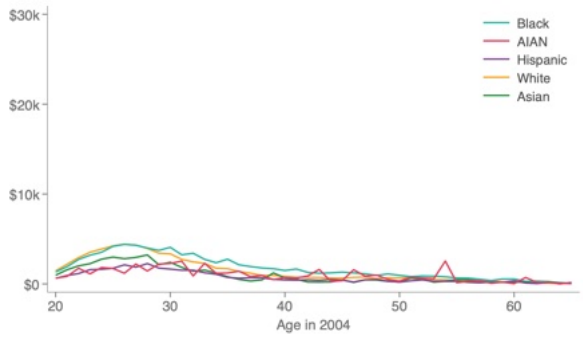
We see similar differences in debt balances by class. Appendix Figure A.19 Panel B shows individuals in the bottom quintile of the parental income distribution have $66,820 in balances, in contrast to $184,890 for those whose parents were in the top quintile of the income distribution—patterns that broadly mirror the differences in credit scores for these groups. Appendix Figure A.19 Panel C presents similar patterns by parental education. Finally, Appendix Figure A.19 Panel D 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.[70] 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 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.

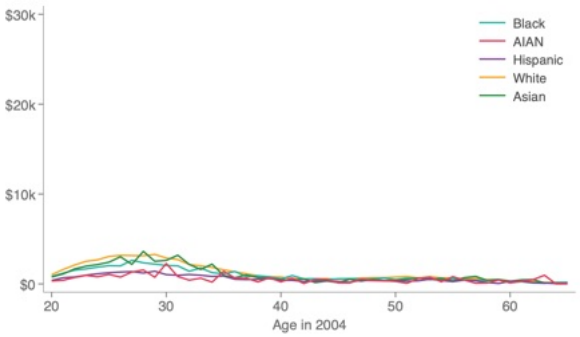
[70]The lower auto and mortgage debts align with lower rates of homeownership and car ownership. Among 2015–2020 ACS respondents in our intergenerational sample with parents at the 25th percentile of household income, 89% of Black individuals owned cars and 41% owned houses, in contrast to 97% and 67%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

FIGURE A.20
Student Debt by Year and Race

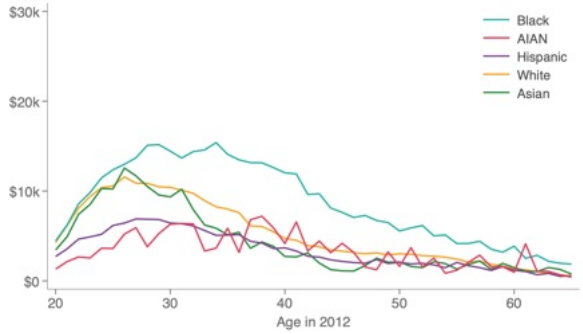
A. Female (2004)



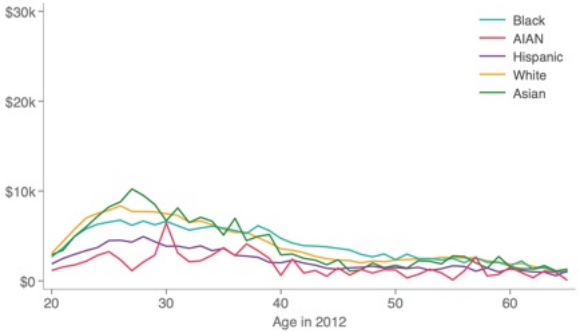
B. Male (2004)



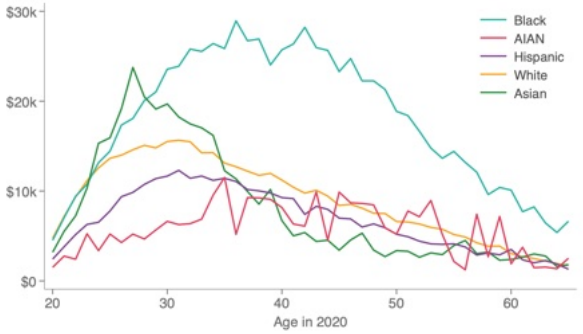
C. Female (2012)



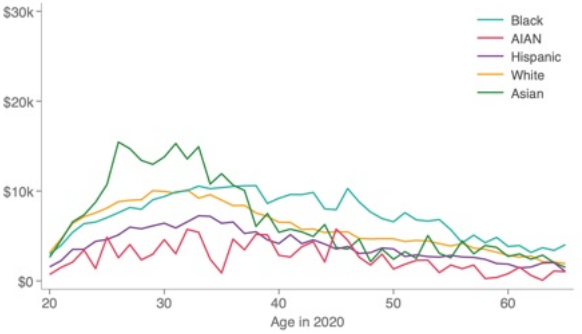
D. Male (2012)



E. Female (2020)



F. Male (2020)



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

Appendix Figure A.20 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 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 0.78 and 0.87), 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 US, 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 US between credit scores and auto balances. In contrast to these formal sector balances, we find a correlation of -0.32 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.

TABLE A.11
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.

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.11 shows that Black and Hispanic individuals have much lower credit limits. This remains true even when we condition on income and past repayment. Consequentially, we see higher rates of credit card utilization among Black people (46%) than White people (29%) in our intergenerational sample in 2020.

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 I 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. Appendix Figure A.2 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.[71]

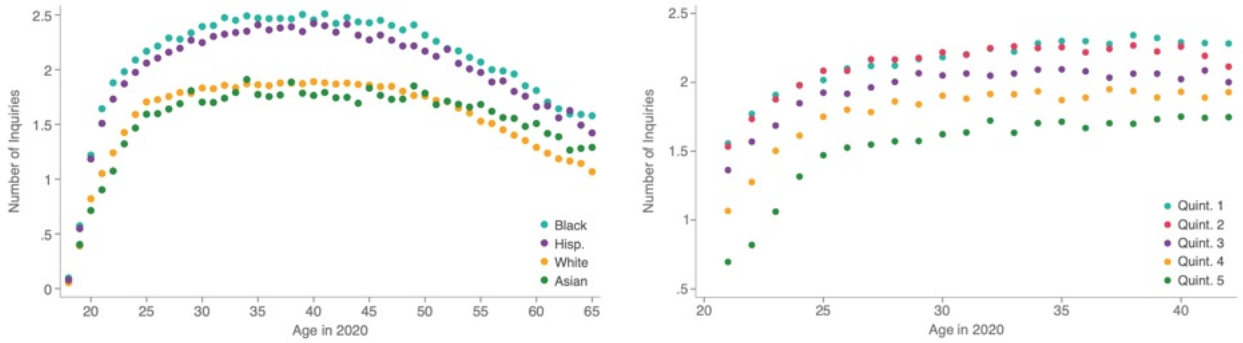
What are the types of credit that initially bring people into the credit market? Overall, most people obtain their first tradeline through a credit card, followed by a student loan. However, Black individuals in particular are more likely to have their first tradeline arise through a student loan. To 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 I Panel A, 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.

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

FIGURE A.21
Number of Inquiries by Age

A. Inquiries by Race **B. Inquiries by Parental Income Quintile**



Notes: This figure presents the number of credit inquiries by age in the population sample in 2020. Panel A presents inquiries by race. AIAN is omitted due to sample size. Panel B presents inquiries by parental income quintile, restricting to the birth cohorts we are able to match to parents.

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. Appendix Figure A.21 Panels A 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 B 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. Appendix Table A.12 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 US adults, 6.9% of Black individuals have used a payday loan in the last year, in contrast to 2.3% for White individuals.[72] 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.

[72]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.

TABLE A.12
Alternative Credit Usage by Race (Survey of Consumer Finances)

	Payday Loan			
	(1)	(2)	(3)	(4)
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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

F Role of Credit Terms

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.[73] 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

[73]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.

per year in extra interest. In Appendix Table A.13, 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 (Columns 5 and 6).[74]

TABLE A.13
Differences in Average Interest Rate by Race and Tradeline

	Credit Card	Auto Loan	Mortgage	Credit Card	Auto Loan	Mortgage	Credit Card	Auto Loan	Mortgage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
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.

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 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.[75] Because the gaps in delinquency emerge

[74]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.

[75]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

on products whose terms are standardized across groups, it is unlikely they drive the gaps in credit access we observe.[76] Rather, the key question is what explains the non-repayment outcomes that occur in one's twenties primarily on items not underwritten by credit scores, such as student loans and utility bills sent to collections.

G Nonlinear Decomposition Method

We use a semiparametric decomposition method following DiNardo, Fortin and Lemieux (1996). Let Y_i denote the outcome of interest, $G_i \in \{W, B\}$ denote group membership, and X_i denote a vector of explanatory variables. For exposition, consider the Black-White gap in mean outcomes, $E[Y_i \mid G_i = W] - E[Y_i \mid G_i = B]$. The decomposition compares the observed Black mean to a counterfactual mean in which Black individuals retain the Black conditional outcome function, $E[Y_i \mid G_i = B, X_i = x]$, but have the White distribution of X_i:

$$E[Y_i \mid G_i = W] - E[Y_i \mid G_i = B] = \underbrace{E[Y_i \mid G_i = B, F_{X|W}] - E[Y_i \mid G_i = B]}_{\text{explained by Black-White differences in } X_i} + \underbrace{E[Y_i \mid G_i = W] - E[Y_i \mid G_i = B, F_{X|W}]}_{\text{remaining gap conditional on } X_i}.$$

The first term is estimated by reweighting Black observations so that their covariate distribution matches the covariate distribution of White observations. The counterfactual mean can be written as

$$\begin{aligned} E[Y_i \mid G_i = B, F_{X|W}] &= \int E[Y_i \mid G_i = B, X_i = x] \, dF_{X|W}(x) \\ &= \int E[Y_i \mid G_i = B, X_i = x] \, \psi(x) \, dF_{X|B}(x), \end{aligned}$$

where $\psi(x)$ is the density-ratio weight that transforms the Black distribution of X_i into the White distribution:

$$\psi(x) = \frac{dF_{X|W}(x)}{dF_{X|B}(x)} = \frac{\Pr(G_i = W \mid X_i = x)/\Pr(G_i = W)}{\Pr(G_i = B \mid X_i = x)/\Pr(G_i = B)}.$$

In practice, we estimate $\Pr(G_i = W \mid X_i = x)$ using a logit model in the pooled Black and White sample and assign each Black observation the estimated weight

$$\hat{\psi}_i = \frac{\hat{p}(X_i)/(1 - \hat{p}(X_i))}{\hat{\Pr}(G_i = W)/\hat{\Pr}(G_i = B)}.$$

they find racial disparities in auto loans. Appendix Table A.13 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.

[76] 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 in 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 VI when studying differential use of alternative financial services such as payday loans.

The counterfactual mean is then the weighted Black mean,

$$\widehat{E}[Y_i \mid G_i = B, F_{X|W}] = \frac{\sum_{i:G_i=B} \hat{\psi}_i Y_i}{\sum_{i:G_i=B} \hat{\psi}_i}.$$

The share of the Black-White gap explained by X_i is the change in the Black mean induced by the reweighting, divided by the observed Black-White gap. This decomposition requires common support: the counterfactual is only well-defined for values of X_i observed with positive probability in both groups.

We use this procedure in Section III to decompose credit-score gaps sequentially. Let $X_i^{(1)}$ denote authorized-user variables, $X_i^{(2)}$ add early "pre-delinquency" tradeline-accrual variables, $X_i^{(3)}$ add early balance variables, and $X_i^{(4)}$ add early delinquencies, collections, bankruptcies, and related repayment-history variables. For each step k, we estimate the reweighting function using the cumulative vector $(X_i^{(1)}, \ldots, X_i^{(k)})$ and compute the corresponding counterfactual Black mean. The contribution of each block is the additional reduction in the gap relative to the previous counterfactual mean. For the parental-income gap, we implement the same two-group procedure using above- and below-median parental income groups. For hometown credit-score gaps, where the object is a variance across many groups rather than a two-group mean difference, we instead report the reduction in the variance of hometown fixed effects after adding the same blocks of variables.

We also use this approach to decompose repayment gaps by income without imposing the linear repayment function used in the main text. In a row comparing group A to group B, we set Y_i equal to an indicator for repayment, set X_i equal to the relevant income measure, and reweight group B so that its income distribution matches that of group A. This produces the mean repayment rate group B would have if it retained its own repayment function conditional on income but had group A's income distribution. Appendix Table A.14 reports the resulting fraction of each repayment gap explained by income under increasingly flexible definitions of the income distribution. The linear functional-form approach and the semiparametric reweighting approach yield similar estimates.

Finally, Appendix Table A.7 uses related standardization weights to study repayment gaps conditional on parental income and credit scores. Let Z_i denote parental income or the credit score, and let F_Z denote the pooled national distribution of Z_i. For each group g, we construct weights proportional to $dF_Z(z)/dF_{Z|g}(z)$ and compute standardized repayment means. This procedure compares groups after equalizing the distribution of parental income or credit scores, so the remaining repayment gaps are not mechanically driven by differences in those conditioning variables.

TABLE A.14
Nonlinear Decomposition of Repayment Gaps by Income (2008)

	Intergenerational Sample				
	Gap	Explained			
	(1)	(2)	(3)	(4)	(5)
White-Black	0.37	4%	20%	22%	12%
White-Asian	-0.13	2%	-3%	2%	13%
White-Hispanic	0.19	6%	19%	20%	15%
High-low par. income	0.27	5%	5%	5%	8%
N	38,490,000	38,490,000	38,490,000	38,490,000	38,490,000
Income		Average	Quintiles	Deciles	Ranks

Notes: This table reports semiparametric decompositions of repayment gaps using the reweighting procedure described in Appendix G. Repayment is defined as having no 90+ day late payment between 2004 and 2008. For each row comparing group *A* to group *B*, Column 1 reports the difference in average repayment rates between the two groups. Columns 2–5 reweight groups *A* and *B* so that their income distributions match that of the national income distribution and report the percentage of the gap explained by the resulting change in average repayment rate. Column 2 uses average family income rank from 2004–2008. Columns 3–5 use increasingly flexible specifications of the income distribution based on income quintiles, deciles, and ranks.

H Proofs of Upper Bounds

We assume the following:

$$\text{Cov}(\bar{y}_g, \bar{\theta}_g) \geq 0 \tag{H.19}$$

$$\text{Cov}(y_i, \theta_i | G_i = g) \geq 0, \tag{H.20}$$

for all groups, g.

Let $\tilde{\alpha}$ and $\tilde{\alpha}_H$ denote estimands from an OLS regressions of repayment against income at the individual and hometown-means levels, respectively:

$$\tilde{\alpha} = \alpha + \frac{\text{Cov}(y_i, \theta_i)}{\text{Var}(y_i)} \tag{H.21}$$

$$\tilde{\alpha}_H = \alpha + \frac{\text{Cov}(\bar{y}_h, \bar{\theta}_h)}{\text{Var}(\bar{y}_h)}. \tag{H.22}$$

Proof of $\tilde{\lambda}_y^{BW} \geq \lambda_y^{BW}$: By the law of total covariance, (H.19) and (H.20) imply $\text{Cov}(y_i, \theta_i)$ must be positive, which means $\tilde{\alpha} \geq \alpha$. For the case where $\Delta r > 0$ and $\Delta y > 0$, we have

$$\begin{aligned}
\tilde{\lambda}_y^{BW} &= \tilde{\alpha}\Delta y && \text{(H.23)}\\
&= \left(\alpha + \frac{\text{Cov}(y_i, \theta_i)}{\text{Var}(y_i)}\right)\Delta y && \text{(H.24)}\\
&= \lambda_y^{BW} + \left(\frac{\text{Cov}(y_i, \theta_i)}{\text{Var}(y_i)}\right)\Delta y \geq \lambda_y^{BW}. && \text{(H.25)}
\end{aligned}$$

Proof of $\tilde{\lambda}_y^h \geq \lambda_y^h$:

$$\begin{aligned}
\tilde{\lambda}_y^h \equiv \text{Var}(\tilde{\alpha}_H \bar{y}_h) &= \tilde{\alpha}_H^2 \text{Var}(\bar{y}_h) && \text{(H.26)}\\
&= \left(\alpha + \frac{\text{Cov}(\bar{y}_h, \bar{\theta}_h)}{\text{Var}(\bar{y}_h)}\right)^2 \text{Var}(\bar{y}_h) && \text{(H.27)}\\
&= \alpha^2 \text{Var}(\bar{y}_h) + 2\alpha \text{Cov}(\bar{y}_h, \bar{\theta}_h) + \frac{\text{Cov}(\bar{y}_h, \bar{\theta}_h)^2}{\text{Var}(\bar{y}_h)} && \text{(H.28)}\\
&= \lambda_y^h + \frac{\text{Cov}(\bar{y}_h, \bar{\theta}_h)^2}{\text{Var}(\bar{y}_h)} \geq \lambda_y^h, && \text{(H.29)}
\end{aligned}$$

where the last inequality holds because $\text{Cov}(\bar{y}_h, \bar{\theta}_h) \geq 0$ by assumption.

Proof that the OLS coefficient on $e_i \cdot \bar{r}$ is a lower bound on κ: Let $x_i \equiv e_i \cdot \bar{r}$. Consider the system

$$y_i = \zeta x_i + \nu_i, \tag{H.30}$$

$$r_i = \alpha y_i + \kappa x_i + \varepsilon_i. \tag{H.31}$$

Assume: (i) $\text{Cov}(x_i, \nu_i) = 0$, (ii) $\text{Cov}(\varepsilon_i, \nu_i) \geq 0$, (iii) $\zeta > 0$, and that x_i is exogenous with respect to ε_i, so $\text{Cov}(x_i, \varepsilon_i) = 0$.

Let κ_{OLS} denote the population OLS coefficient on x_i in the regression of r_i on (y_i, x_i).

Project x_i linearly onto y_i:

$$x_i = \pi y_i + \tilde{x}_i, \quad \text{where } \text{Cov}(\tilde{x}_i, y_i) = 0.$$

By the Frisch–Waugh–Lovell theorem,

$$\kappa_{\text{OLS}} = \frac{\text{Cov}(r_i, \tilde{x}_i)}{\text{Var}(\tilde{x}_i)}.$$

Substituting (H.31) into the numerator,

$$\text{Cov}(r_i, \tilde{x}_i) = \alpha\, \text{Cov}(y_i, \tilde{x}_i) + \kappa\, \text{Cov}(x_i, \tilde{x}_i) + \text{Cov}(\varepsilon_i, \tilde{x}_i).$$

The first term is zero by construction, and since $x_i = \pi y_i + \tilde{x}_i$, $\text{Cov}(x_i, \tilde{x}_i) = \text{Var}(\tilde{x}_i)$. Thus,

$$\kappa_{\text{OLS}} = \kappa + \frac{\text{Cov}(\varepsilon_i, \tilde{x}_i)}{\text{Var}(\tilde{x}_i)}.$$

To sign the bias term, note that

$$\text{Cov}(\varepsilon_i, \tilde{x}_i) = \text{Cov}(\varepsilon_i, x_i) - \pi \, \text{Cov}(\varepsilon_i, y_i).$$

By exogeneity, $\text{Cov}(\varepsilon_i, x_i) = 0$. Using (H.30),

$$\text{Cov}(\varepsilon_i, y_i) = \zeta \, \text{Cov}(\varepsilon_i, x_i) + \text{Cov}(\varepsilon_i, \nu_i) = \text{Cov}(\varepsilon_i, \nu_i) \geq 0.$$

The projection coefficient π satisfies

$$\pi = \frac{\text{Cov}(x_i, y_i)}{\text{Var}(y_i)} = \frac{\zeta \, \text{Var}(x_i)}{\text{Var}(y_i)} > 0,$$

where the equality uses $\text{Cov}(x_i, \nu_i) = 0$ and the inequality follows from $\zeta > 0$.

Hence,

$$\text{Cov}(\varepsilon_i, \tilde{x}_i) = -\pi \, \text{Cov}(\varepsilon_i, \nu_i) \leq 0,$$

which implies

$$\kappa_{\text{OLS}} \leq \kappa.$$

Meanwhile, note that from FWL and Equation (H.30), we have

$$\alpha^{OLS} = \alpha + \frac{\text{Cov}(\varepsilon_i, \nu_i)}{\text{Var}(\nu_i)} \geq \alpha$$

in the regression of r_i on y_i and x_i, where x_i is the mover exposure measure after partialling out the common controls.

This establishes that in the OLS regression of $r_i \sim y_i + e_i \cdot \bar{r}$, the coefficient on y_i is an upper bound on α and the coefficient on $x_i = e_i \cdot \bar{r}$ is a lower bound on κ.

I Further Discussion of Potential Determinants of Delinquencies

I.A 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 the previous results show that observed income profiles account for only part of the repayment gaps, 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 (Chetty et al., 2026*a*) and non-repayment (Appendix Figure A.23).

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. In Appendix Table A.15, Columns 1–5 show a regression of the incidence of unexpected expenses by category on binary indicators for being Black, parental education of high school or less, and below median childhood county repayment rate. We see that there are lower unexpected expenses for those with low parental education, possibly due to lower rates of home ownership. Also, we find higher rates of unexpected childcare and school expenses for Black respondents. However, across the other categories, there are not many significantly different incidences of unexpected expenses.

Next, we examine whether differences in unexpected expenses can explain the gaps in delinquency by race, class, and hometown. In Column 6, we start with a regression of delinquency on the same binary indicators. In Column 7, we add a vector of controls for the different types of unexpected private expenses to the regression. We find that the gaps in delinquency by race and hometown decrease by 4% and 29%, respectively, while the gap by class increases by 46%. Broadly, it appears that even if there is some evidence for small differences in expenditure shocks, these measures account for little of the repayment gaps we observe.

TABLE A.15
Unexpected Expenses (Prolific Survey)

	Unexpected Expense						
	Home	Medical or Legal	Childcare	Auto	Other	Missed Payment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Black	-0.027	0.015	0.050**	-0.012	-0.037*	0.124***	0.120***
	(0.039)	(0.038)	(0.022)	(0.038)	(0.020)	(0.039)	(0.039)
Par. High School or Less	-0.107***	-0.045	-0.037	-0.055	0.001	0.070*	0.102**
	(0.041)	(0.040)	(0.023)	(0.040)	(0.021)	(0.041)	(0.041)
Hometown Below Med. Repay	0.071*	-0.038	0.018	-0.009	0.004	0.036	0.025
	(0.038)	(0.037)	(0.022)	(0.036)	(0.020)	(0.038)	(0.037)
Education Control	X	X	X	X	X	X	X
Unexpected Expenses							X
N	702	702	702	702	702	702	702
R^2	0.032	0.017	0.041	0.034	0.008	0.021	0.091

Notes: This table reports estimated coefficients from OLS regressions using data from our Prolific survey of 702 US adults aged 22-30 that relate three demographic factors to incidence of unexpected expenses and missed payments. The regressions include a Black indicator, an indicator of parental education being a high school diploma or less, an indicator for below median debt-repayment rate in the respondent's childhood county, and a continuous measure of the respondent's own educational attainment (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). In Columns 1–5, the dependent variables are indicators for experiencing unexpected expenses, which have been grouped into home expenses (home and/or appliance repair; high utility bills; broken electronics; housing/needing to move), medical or legal expenses (medical; traffic ticket, fine, legal fee; and identity theft/fraud/crime), childcare or school expenses, auto repair expenses, and other expenses. In Columns 6–7, the dependent variable equals 1 if the respondent reports missing any loan or bill payment in the past 12 months. In Column 7, we add indicators for experiencing the 11 categories of unexpected expenses above and an indicator for having no unexpected expenses. Statistical significance is denoted *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

I.B Financial Literacy and Cognitive Skills

This appendix provides greater detail on our exploration of the potential role of measures of financial literacy in mediating the differences in repayment rates across groups. We note at the outset that 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]

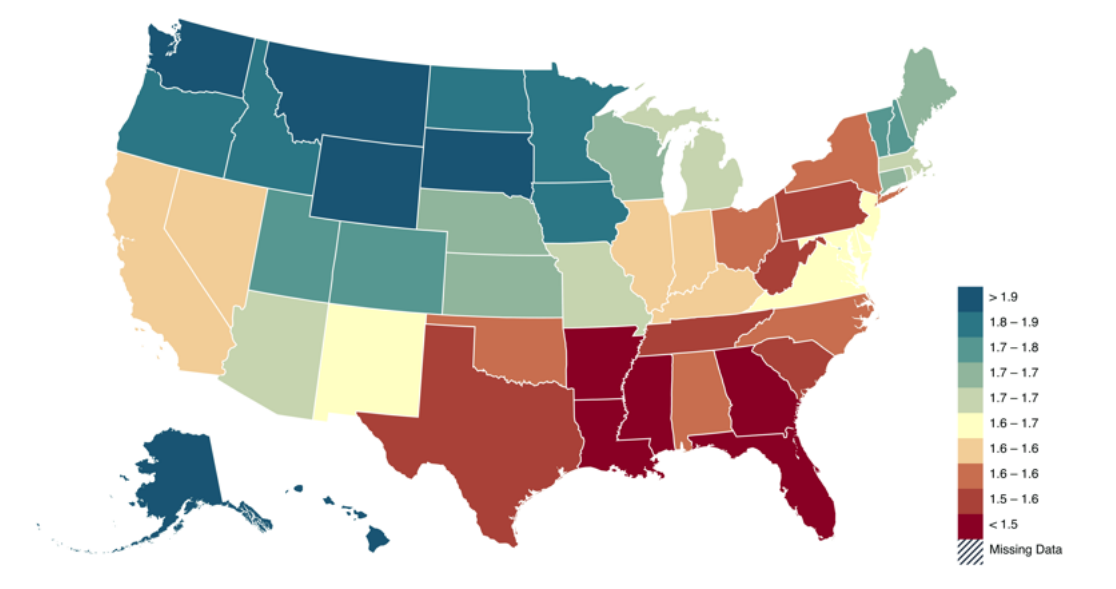
2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? [Possible answers: more than/less than/same as today]

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

There is some evidence that financial literacy and education interventions generate positive outcomes in the credit market (Kaiser et al., 2022). Mandatory high school financial literacy courses are associated with lower non-student debt, fewer defaults, and higher credit scores among 18-21 year olds (Brown et al., 2016; Urban et al., 2020) and shift borrowing for post-secondary education to lower-cost options (Stoddard and Urban, 2020), without any evidence of adverse effects on graduation rates (Urban, 2023); targeted information about accumulated student-loan debt increased GPAs and retention among college borrowers (Stoddard, Urban and Schmeiser, 2017); and information interventions for working people increase retirement planning, emergency saving, and budgeting (Collins and Urban, 2016).[77]

[77] We note that credit-related effects are not uniformly positive: a school-based financial education experiment in Brazil improved budgeting and saving but increased some expensive consumer purchases on credit (Bruhn et al., 2016). These effects may also be concentrated in the short run: for example, Harvey and Urban (2023) find no effect on retirement account holdings or amounts saved among 25-40 year olds after high school financial education. There is also some concern that these effects are driven by groups with better credit outcomes ex-ante, which could increase delinquency gaps. There is suggestive evidence that high school financial education programs with positive overall effects decrease subjective measures of financial well-being by altering expectations among non-college goers (Burke, Collins and Urban, 2023). In addition, an analysis of high school course catalogs shows that Whiter student bodies, lower poverty rates, higher math scores, and higher student-teacher ratios at high schools are positively correlated with financial literacy requirements (Urban, 2024).

FIGURE A.22
"Big 3" Financial Literacy Score by State (NFCS)



Notes: This figure reports the average score on the "Big 3" financial-literacy questions across US 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.

Previous literature has also documented that young adults in particular tend to score lower on measures of financial literacy. On average, 33% of US 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.[78] It has also documented that financial literacy is declining over time, especially among young people, women, and Black people (Urban and Valdes, 2022). 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 US states using data from the NFCS, shown in the map in Appendix Figure A.22. We find a state-level correlation of 0.77 with both our measures of repayment and repayment conditional on income in 2020. Places that promote repayment tend to also be places where people score more highly on these measures of financial literacy.

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

TABLE A.16
Financial Literacy and Non Repayment (SCF)

	Missed Payment				
	(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: Diversification" 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." "Financial Literacy: Interest" 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?" 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.

People who correctly respond to financial literacy questions are less likely to fall delinquent. Appendix Table A.16 presents a regression of self-reported delinquency[79] in the SCF against responses to the Big 3

[79]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?"

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.9 shows that Black individuals and those from areas of the US 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 US with higher debt repayment rates.[80] 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 4 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 13.6 percentage points more likely to have missed a payment, those whose parents have one more year of education are 1.3 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 0.52 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 5 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

[80] The correct answer is seven years.

non-repayment but have only a modest impact on the relationship between race, class, and hometown and having missed a payment. The coefficients on all three demographic indicators remain constant.

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.

I.C Correlates of High Repayment Across Geography

This Appendix provides an exploration of the geographic correlates of repayment rates across counties in the US. In Appendix Figure A.23, we plot the correlations of a range of variables with repayment and repayment conditional on income for individuals growing up at the 25th percentile of family income in 2020 in our intergenerational sample (born between 1978 and 1985). We split the correlates into four categories: economic, education, family structure, and social capital.

We begin with economic correlates from Chetty et al. (2026*a*). The population density in 2010, or total county population divided by square miles, has a very small correlation with repayment (0.10). We find stronger correlations with the unemployment rate (-0.46) and the median household income (0.37), both of which are calculated from Census data in 2010. These correlations persist even when focusing on repayment after conditioning on one's income, with correlations of (0.31, -0.26, and 0.32, respectively).

Next, we look at educational correlations. We use the average third grade math scores in 2013 from the Stanford Education Data Archive and fraction of 25 year olds with a Bachelor's degree in 2010 from the Decennial Census. We find that educational correlates are about as strong as the strongest economic correlates: 0.37 for third grade math scores and 0.28 for share college grads. While these correlations are somewhat large, it does not appear that some latent measure of ability (as measured by math scores and college graduation rates) can account for the full distribution of repayment gaps across place.

Third, we turn to measures of family structure including the 2010 share of single parent households (Chetty et al., 2026*a*) and 2000 divorce rate (National Center for Family & Marriage Research, 2016). Similarly to upward income mobility in (Chetty et al., 2026*a*), the share of single households is very highly correlated with repayment (-0.63). The divorce rate has a slightly smaller correlation that is similar to the correlation with economic and educational variables (-0.41).

Fourth, we explore the correlation with social capital measures. Of all variables we examine, the strongest correlate is a measure of social capital constructed from Facebook (Meta) data called economic connectedness: the fraction of below-median-SES children's friends who are above-median SES (Chetty et al., 2022). Economic connectedness has a correlation of 0.66 with repayment. We also correlate repayment with the support ratio and clustering (Chetty et al., 2022) and the Census Form Return Rate in 2010 (Chetty et al., 2026*a*). The support ratio is the rate at which pairs of friends in a community have other friends in common, while clustering is the share of an individual's friend pairs who are friends with each other. County repayment rates have a correlation of -0.20 with their average support ratio, 0.08 with the clustering rate, and 0.32 with the Census return rate. When we look at the repayment conditional on income,

economic connectedness remains positively correlated, even though its magnitude is attenuated (0.31).

FIGURE A.23
Correlates of Hometown Estimates

Notes: This figure presents correlation coefficients between various county-level covariates and our county-level estimates of repayment at the 25th percentile of parental income (pooling across all racial groups and weighted by population). All rows report the magnitude of the correlation estimate. The filled shapes represent positive correlations, and the unfilled shapes represent negative correlations. The yellow circles report the average repayment in 2008. The blue triangles report the average repayment in 2008 residualized on 2004 income rank.

I.D Risk-Sharing Networks

This appendix provides greater detail on our exploration of the potential role of risk-sharing networks in mediating the differences in repayment rates across groups. 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. Controlling for age, education, parental education, and hometown, Black young adults were asked for financial help 1.6 more times in the last 3 years than White young adults. They have given such financial help 0.77 more often than White individuals, or 45% more than the unconditional White average of 1.72. Most of this is driven by a higher likelihood of giving to a sibling (42% vs 9%) and a parent (21% vs 18%). Appendix Table A.10 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.[81] We find corroborating evidence of these patterns in the SCF as well: conditional on income, Black young adults are more likely than White young adults to give financial support to family and friends.

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 $464 less from family/friends in our Prolific Survey. This is documented in Column 4 of Appendix Table A.10, which shows that Black respondents, those with low parental education, and those from low repayment hometowns are all less able to borrow (although the hometown coefficient is imprecise). 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.

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.[82] 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.[83]

Do these differences in informal insurance obligations and parental obligations correlate with non-repayment? Column 5 of Table A.10 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. This 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.

We then assess the impact of controlling for transfers to family and friends. Column 6 introduces controls for the amount of financial assistance the individual has given and the amount they think they could borrow from family and friends in an emergency. This reduces the Black-White race gap by almost one-third, as access to liquid money and giving financial assistance are associated with non-repayment. Black

[81] By contrast, those whose parents have lower education levels give less and are asked for financial help less often – perhaps because they have greater resources.

[82] Charles and Hurst (2002) find that 27% of White home buyers received familial help paying their down payments, as opposed to 7% of Black home buyers.

[83] 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).

young adults are less likely to have access to money through their networks, but more likely to give financial assistance than White young adults. Column 7 adds the number of times they were asked for financial help. We find that including these controls renders the Black-White gap in non-repayment statistically insignificant. However, the key variable driving much of this reduction in the gap is not the amount they give to family or friends, but rather the number of times they were asked for money and the amount they could borrow from family/friends. This suggests that the underlying driver of the patterns may be more related to their ability to obtain resources from people in their network and the overall demand for credit (or insurance) from others in their network, as opposed to greater financial obligations imposed by the network.

In addition to these findings in our Prolific survey, we find qualitatively similar patterns in the SCF.[84] Controlling for an indicator of whether someone gave financial support to others reduces the Black-White gap in repayment by a small amount (7%). Further adding an indicator for whether they think they could borrow $3,000 from friends or family reduces the Black-White gap by 29%. In other words, controlling for a proxy of credit constraints across one's network has a similar effect on the race gaps in early life delinquency as controlling for a decade of tax return information.

We conclude that measures of one's social network and financial relationships within that network have strong predictive power for repayment. Yet, we also find evidence in our Prolific survey that these measures 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. Such a perspective would also be consistent with the fact that we continue to observe large gaps within high-income subsamples of the data. 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.

I.E Culture

> *Action is necessarily integrated into larger assemblages, called here "strategies of action." Culture has an independent causal role because it shapes the capacities from which such strategies of action are constructed. The term "strategy" is not used here in the conventional sense of a plan consciously devised to attain a goal. It is, rather, a general way of organizing action (depending upon a network of kin and friends, for example, or relying on selling one's skills in a market) that might allow one to reach several different life goals. Strategies of action incorporate, and thus depend on, habits, moods, sensibilities, and views of the world (Geertz, 1973). People do not build lines of action from scratch, choosing actions one at a time as efficient means to given ends. Instead, they construct chains of action beginning with at least some prefabricated links. Culture influences action through the shape and organization of those links, not by determining the ends to which they are put.* (Swidler (1986), pps. 276-277)

This appendix provides greater detail on our exploration of the potential role of culture in mediating the differences in repayment rates across groups. Recent work in economics has focused on how people

[84] The SCF does not contain analogous measures of hometown or parental class. For brevity, we omit a table of these regressions.

make decisions, especially under scarcity (Kahneman, 2011; Mullainathan and Shafir, 2013). When there is a shortage of time or money, people operate with a bandwidth tax that compromises their ability to "think slow" and consider optimal ways to respond. Yet that work tells us less about what people actually do under these circumstances. When facing uncertain and new difficult situations, individuals often fall back on their past experiences to help navigate a complex environment, a form of culture that sociologists call a "toolkit" that enables strategic action (Swidler, 1986).[85] 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* (like renting an apartment in a higher poverty area because they don't screen for credit), 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)).

There is a related 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).[86] 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).[87]

Specifically, culture can also include knowledge about the hidden rules of the game required to navigate complex situations (Lareau, Adia Evans and Yee, 2016). Recent work has highlighted the particular difficulties faced when managing the student loan system in the US, 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); related work shows that financial education can operate through attitudes, counseling, goal-setting, and emotionally salient narratives, not only through cognitive financial knowledge (Berg and Zia, 2017; Carpena et al., 2019; Carpena and Zia, 2020). This suggests that poor financial decisions may reflect a lack of guidance on how to navigate complex systems.

Culture can provide a set of fall-back strategies that people use, especially when making decisions under uncertainty or constraints. The main text provides a test that exploits the fact that these strategies likely vary idiosyncratically across places and outcomes. Young adults replicate the delinquency outcomes

[85] The core contribution of Swidler (1986) was to reconceptualize culture away from a notion of one's values towards a perspective that it's a toolkit for navigating one's social environment and shapes the capacity to form strategies.

[86] See also work studying the role of culture in economic outcomes including Carroll, Rhee and Rhee (1999) for the impact of culture on savings behavior and Guiso, Sapienza and Zingales (2009) for its impact on global trade.

[87] Dokko, Li and Hayes (2015) find positive assortative matching based on credit scores and that credit scores are predictive of future separations.

at the tradeline level across place in proportion to childhood exposure. Growing up in places where people are more likely to fall delinquent on student loans versus credit cards leads people to uniquely be more likely to fall delinquent on student loans. This finding echoes findings in earlier work from Chetty and Hendren (2018*a*) that people replicate the entire outcome distributions of income (and college) outcomes across place in proportion to childhood exposure.

Another pathway to testing this theory is to explore how people respond to financial shocks. One potential response is to rely 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; 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, 2016; 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, 2019; 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).

In Section E, 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. Appendix Table A.17 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.

TABLE A.17
Alternative Credit Use (Prolific Survey)

	Alternative Credit Use							
	Payday Loan	Payday App	Auto Title	Pawn Shop	BNPL	Rent-to-Own	Missed Payment	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black	0.094***	0.113***	0.058**	0.023	0.118***	0.043	0.111***	0.046
	(0.034)	(0.034)	(0.025)	(0.022)	(0.039)	(0.027)	(0.040)	(0.038)
Parent Education	0.005	-0.007	-0.006	0.005	-0.019**	-0.004	-0.014*	-0.011
	(0.006)	(0.006)	(0.005)	(0.004)	(0.007)	(0.005)	(0.007)	(0.007)
Chldhd Cnty	0.302	0.097	-0.146	0.296**	0.402*	0.236	0.449**	0.244
Delinq Rate	(0.186)	(0.185)	(0.137)	(0.124)	(0.214)	(0.148)	(0.218)	(0.205)
Education	X	X	X	X	X	X	X	X
Alt Financial Svcs								X
N	702	702	702	702	702	702	702	702
R^2	0.048	0.024	0.017	0.015	0.039	0.015	0.027	0.161

Notes: This table reports OLS regression estimates from our Prolific survey of 702 US adults aged 22–30. The first six columns report 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: (1) payday loan, (2) a wage-advance "payday" app, (3) an auto title loan, (4) a pawn shop loan, (5) buy-now-pay-later financing (BNPL), and (6) 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. Parental and own education are coded as continuous measures (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 next two columns report repayment outcomes: Column 7 regresses a missed payment indicator on the same three explanatory variables (plus continuous education controls); Column 8 adds the six alternative financial services indicators from the first six columns 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.

Columns 7 and 8 of Appendix Table A.17 present 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.[88]

While we cannot discern whether these correlations reflect a causal effect of alternative financial services, our survey results weigh against some potential theories. In particular, the fact that delinquent Black individuals are turning to payday loans suggests their delinquencies are unlikely to reflect only inattention or strategic default.[89] Rather, our results speak to the financial distress and credit constraints faced by many

[88] 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.

[89] 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.

households from disadvantaged groups.