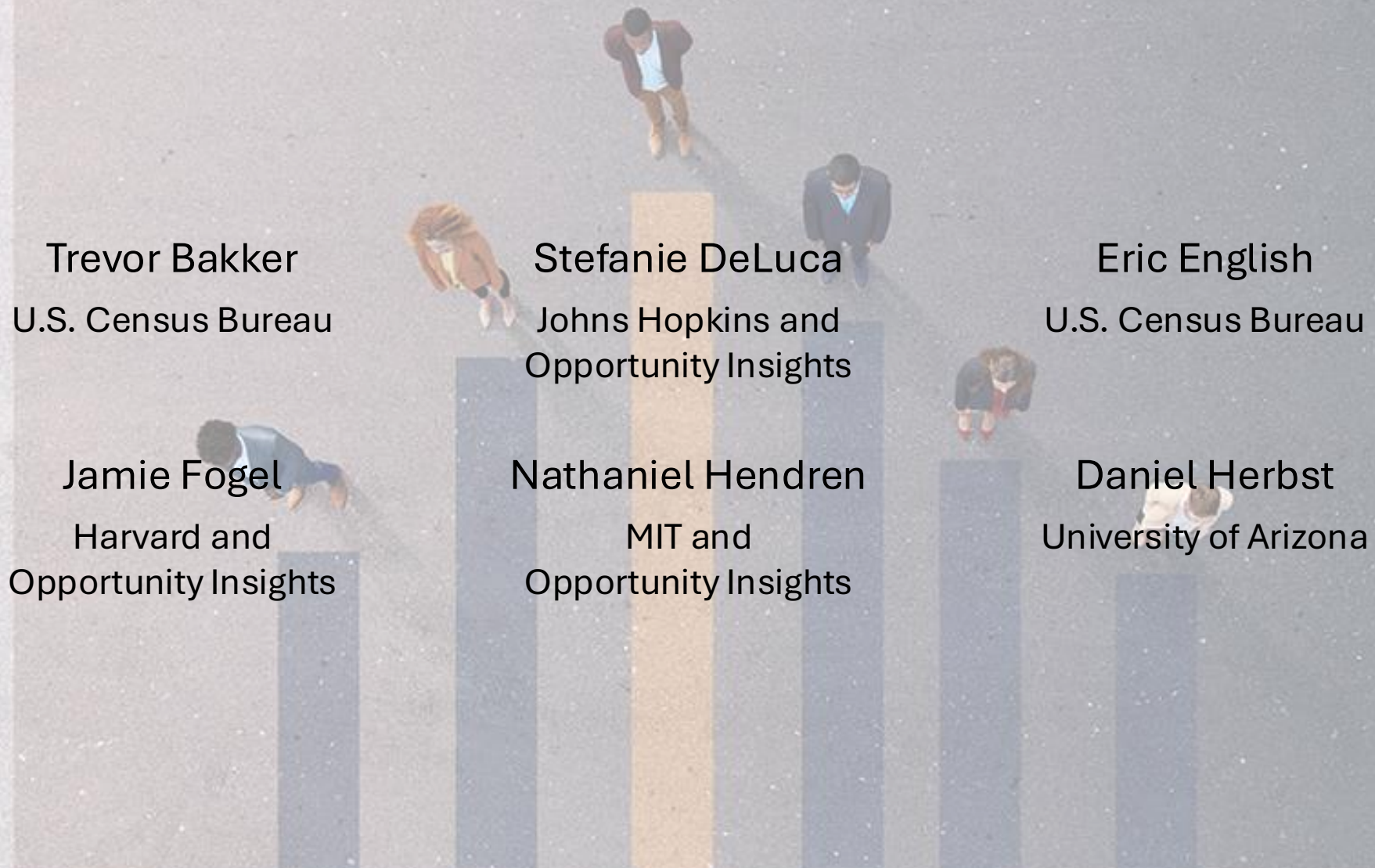


Credit Access in the United States



Trevor Bakker
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DISCLAIMER: Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (Project 7519874: CBDRB-FY24-0345, CBDRB-FY24-CES026-013, CBDRB-FY25-0024, CDRB-FY25-0155, CDRB-FY25-0167, CBDRB-FY25-0220, CBDRB-FY25-0323, CBDRB-FY25-0350).

Introduction

- One's background (race, parental income, hometown) affects outcomes in adulthood
- Access to affordable credit is a pathway to overcome one's starting circumstances and achieve economic opportunity
- **How does one's background affect access to affordable credit? Why?**
- Limited data linking credit records and income/demographics
 - Notable exceptions:
 - SSA Linkage [Federal Reserve Board of Governors (2007), summarized in Avery, Brevoort, and Canner (2009)]
 - LEHD Data [Braxton, Chikhale, Herkenhoff, and Phillips (2023)]
 - HMDA Data [Bhutta and Canner (2013); Bayer, Ferreira, and Ross (2016); Fuster et al., 2022; Bhutta, Hizmo and Ringo, 2024; CFPB Office of Research, 2021; Gerardi, Lambie-Hanson and Willen, 2021; Bhutta and Hizmo, 2021]
 - Consumer Data [Blattner and Nelson (2024)]



Construct linked Credit Bureau and Census/Tax data for 25M+ individuals

Population Sample: 1% sample of US population with SSNs

Intergenerational Sample: Full sample of 1978-85 birth cohorts (Chetty et al. 2020), plus 10% linkage to parents (those aged 55-85 in 2020)

Census and Tax data (1969-2021) provide measures of race, income, education, place...

- Tax data provides income information from W-2s and 1040s (+parent linkage)
- Census data provides race/ethnicity and education from Decennials and ACS

Credit Bureau data person-level attributes file pulled every 4 years from June 2004-2020

- Balances, delinquencies, bankruptcies, and # of tradelines
- By type of credit: mortgages, credit cards, auto loans, and student loans
- Credit score (Vantage 4.0) aims to predict future 90+ day delinquency



Construct linked Credit Bureau and Census/Tax data for 25M+ individuals

Part 1: Measurement of differences in credit access by race, class, and hometown

- Use credit score as measure of credit access (Gibbs et al. 2025 JEL)
- Assess relationship to future 90+ day delinquency by one's background

Part 2: Determinants of credit access

- Study underlying drivers of differences in credit access and delinquency
- Role of income versus factors shaped during childhood



Related Literature

1. Measurement of disparities in credit scores

- Garon (2022); Martinchek (2024); Brevoort, Grimm and Kambara (2015); Bhutta, Hizmo and Ringo (2024); CFPB Office of Research (2021); Gerardi, Lambie-Hanson and Willen (2021); Bhutta and Hizmo (2021); Warren et al. (2024); Stavins (2020); Federal Reserve Board of Governors (2007). Avery, Brevoort, and Canner (2009)

2. Algorithmic fairness and design of credit scores

- Kleinberg, Mullainathan and Raghavan, (2016); Arnold, Dobbie and Hull (2022,2025); Elzayn et al. (2025); Black et al. (2022); Passi and Barocas (2019); Barocas and Selbst (2016); Kleinberg et al. (2018); Obermeyer et al. (2019); Blattner and Nelson (2021); Fuster et al. (2022); Fourcade and Healey (2013)

3. Racial wealth gap and greater financial strain faced by Black and low-income HHs

- Stack (1974); McAdoo (1978); Taylor et al. (1996); Chatters et al. (2008); St. Vil et al (2018); Massey and Denton (2019); Derenoncourt et al. (2024); Chiteji and Hamilton (2002); McKernan et al (2014); Lanuzza (2020); Bartik et al. (2024)

4. Credit and intergenerational mobility

- Hartley, Mazumder, and Rajan (2019); Braxton et al. (2024); Bayer, Charles and Park (2025)

5. Determinants of credit market behavior

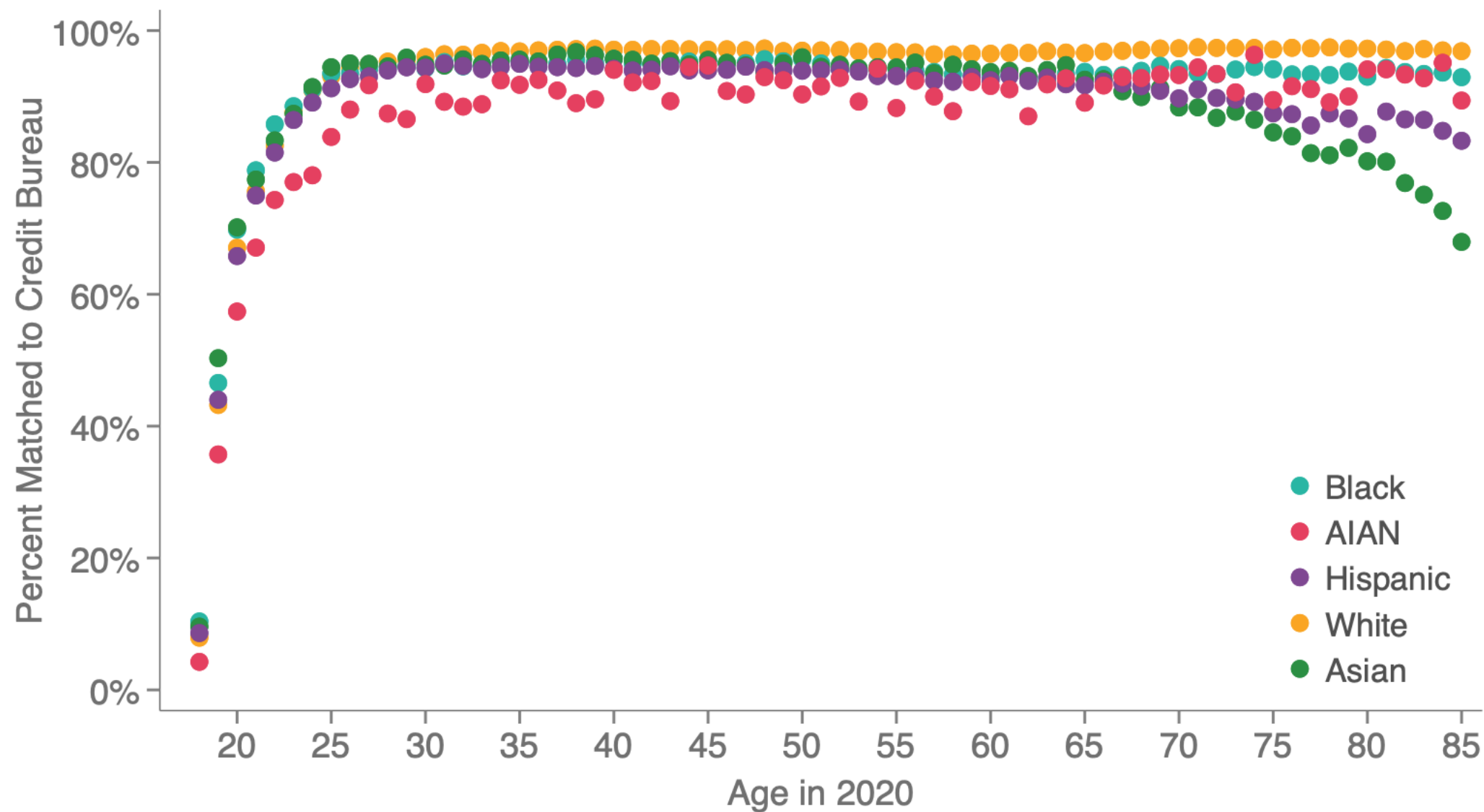
- Lusardi and Mitchell (2014, 2023); Malmendier and Nagel (2011, 2016); Miller and Soo (2020); Malmendier and Wachter (2021), Keys, Mahoney, and Yang (2023); Bartik et al. (2025); Bogan, Kramer, Liao, and Niessen-Ruenzi (2025); Arthi, Richardson and Van Orden (2024); Ganong and Noel (2019); Fulford and Low (2024); Scott-Clayton and Li (2016)

6. Racial bias in lending/credit decisions

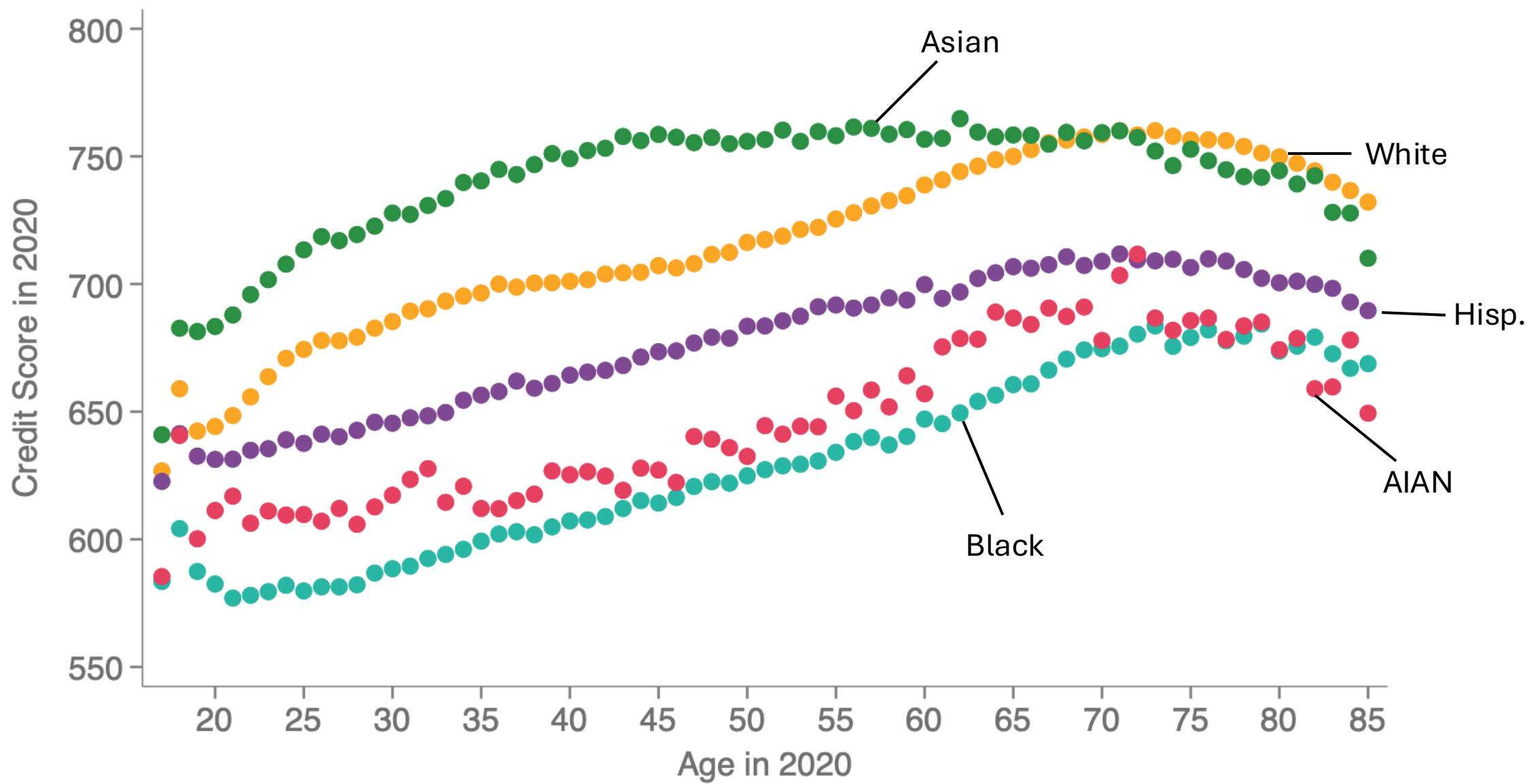
- Munnell et al. (1996); Bostic (1997); Lanning (2021); Butler, Mayer and Weston (2023); Raymond (2024); Bartlett et al. (2022); Argyle et al. (2025); Bhutta and Hizmo (2021); Dobbie et al 2021; Willen and Zhang (2023); Gerardi, Willen and Zhang (2023); Ricks and Sandler (2022); Edelberg (2007); Bhutta, Hizmo and Ringo (2024); Argyle, Indarte, Iverson, and Palmer (2025)



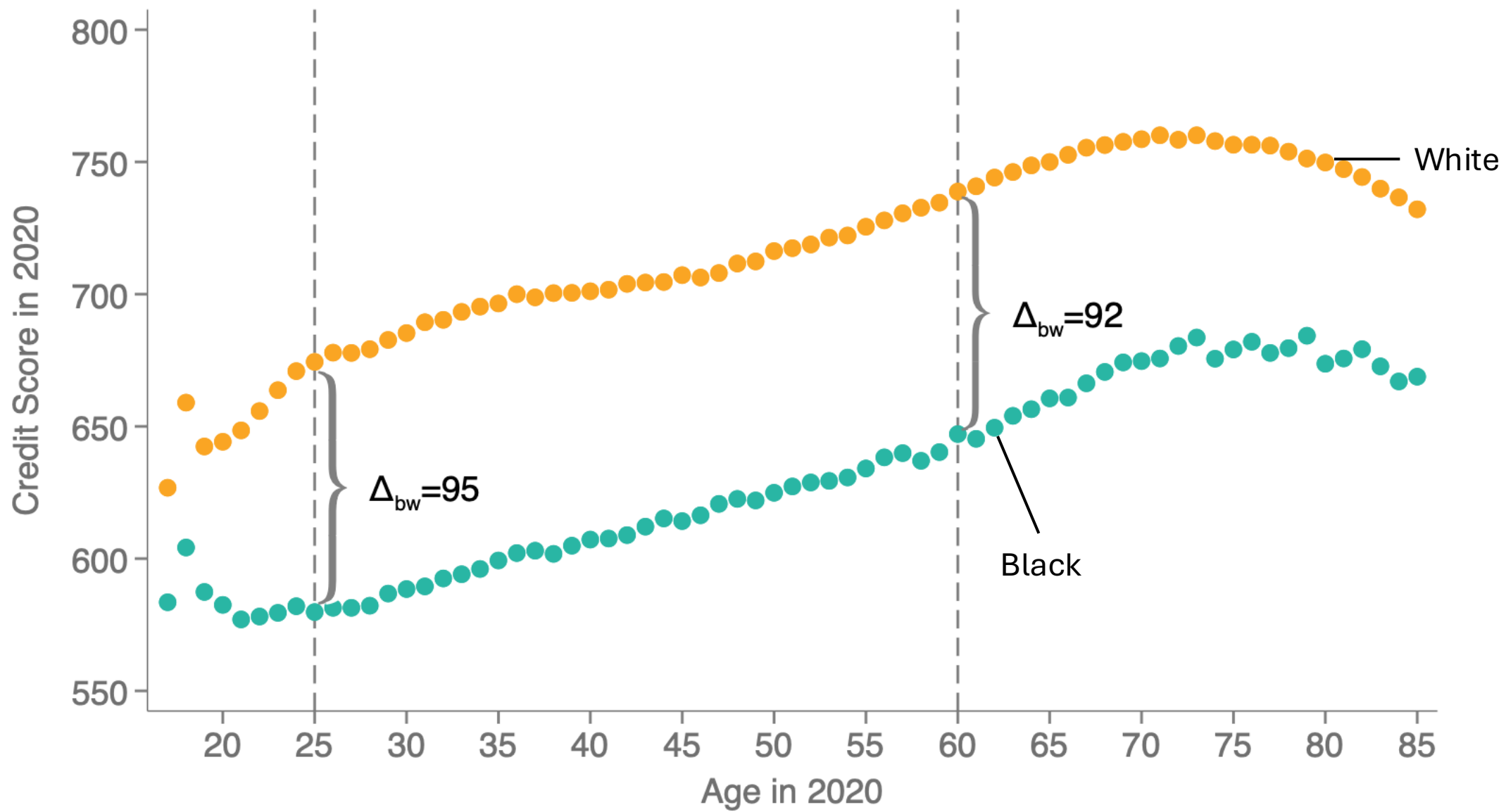
Fraction of People with a Credit File, by Race



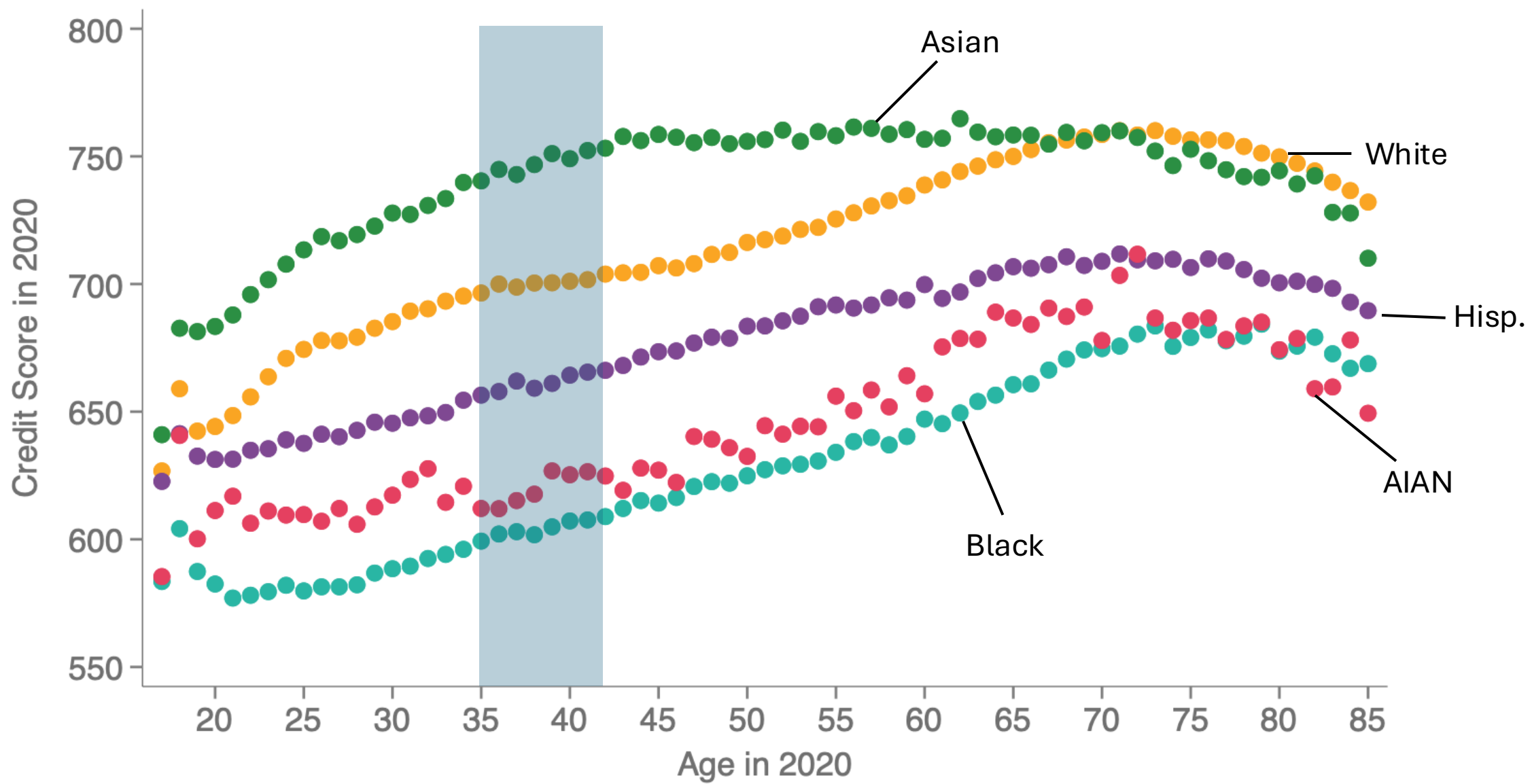
Credit Scores by Age and Race in 2020



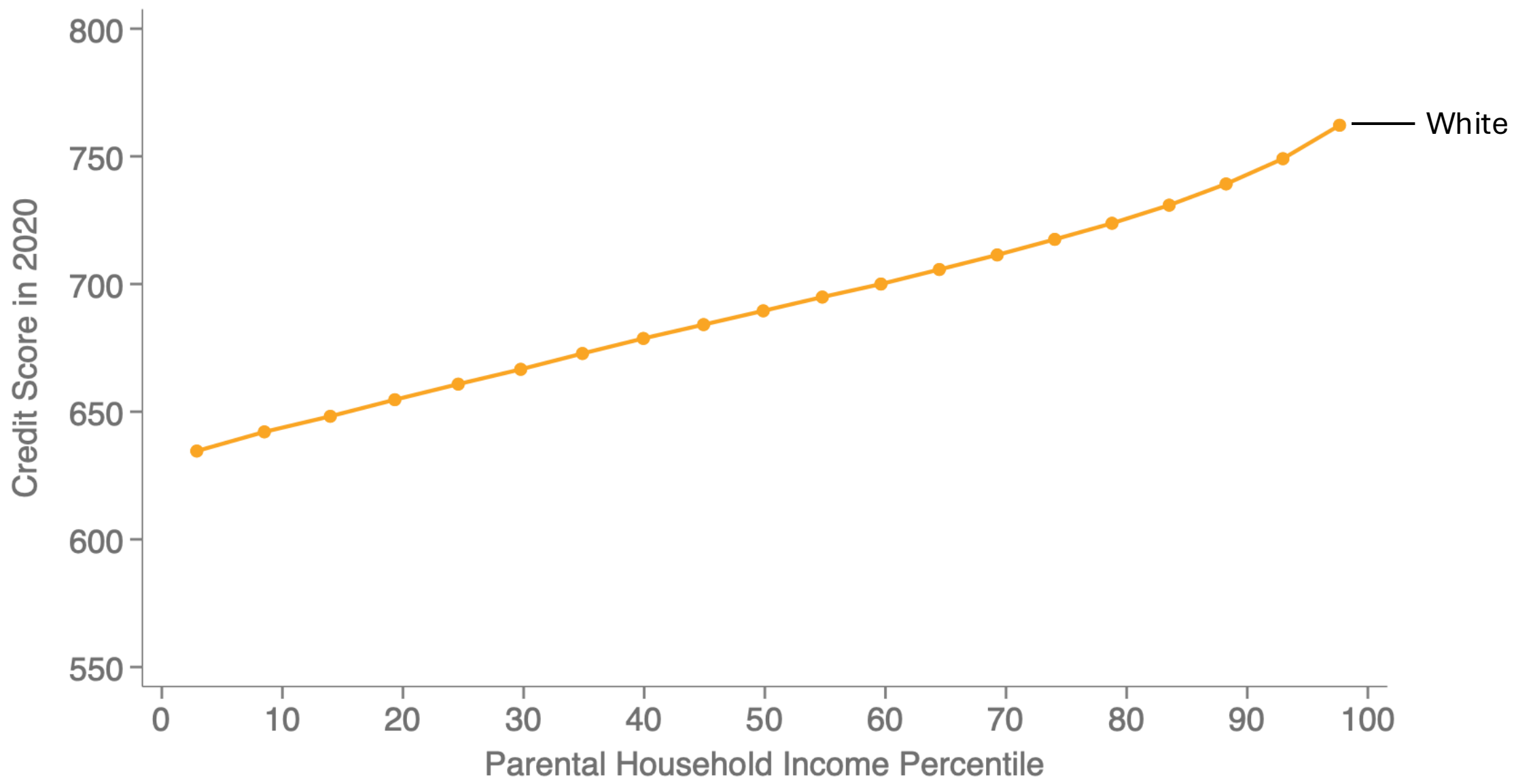
Credit Scores by Age and Race in 2020



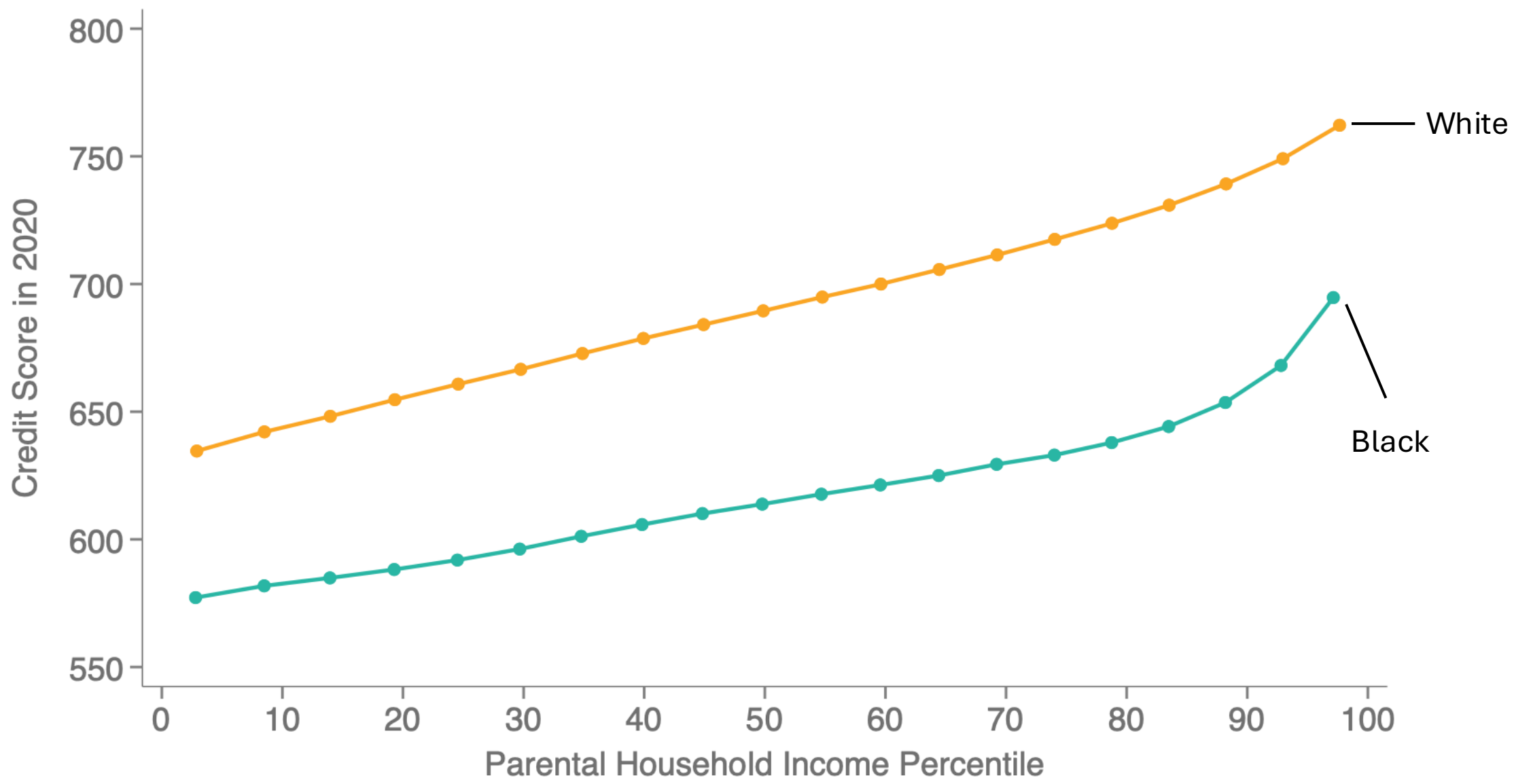
Credit Scores by Age and Race in 2020: Intergenerational Sample



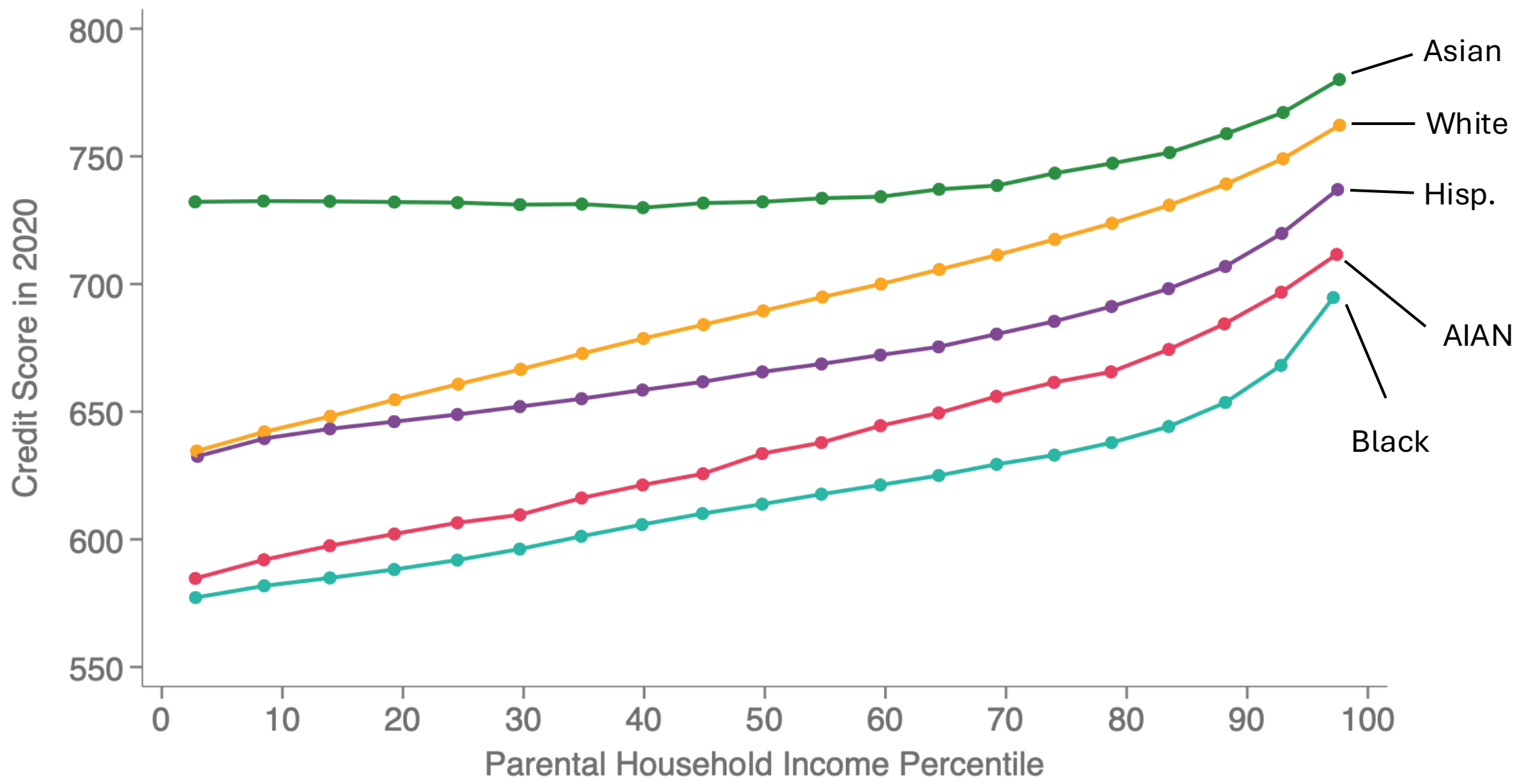
Credit Scores by Race and Parental Income 2020



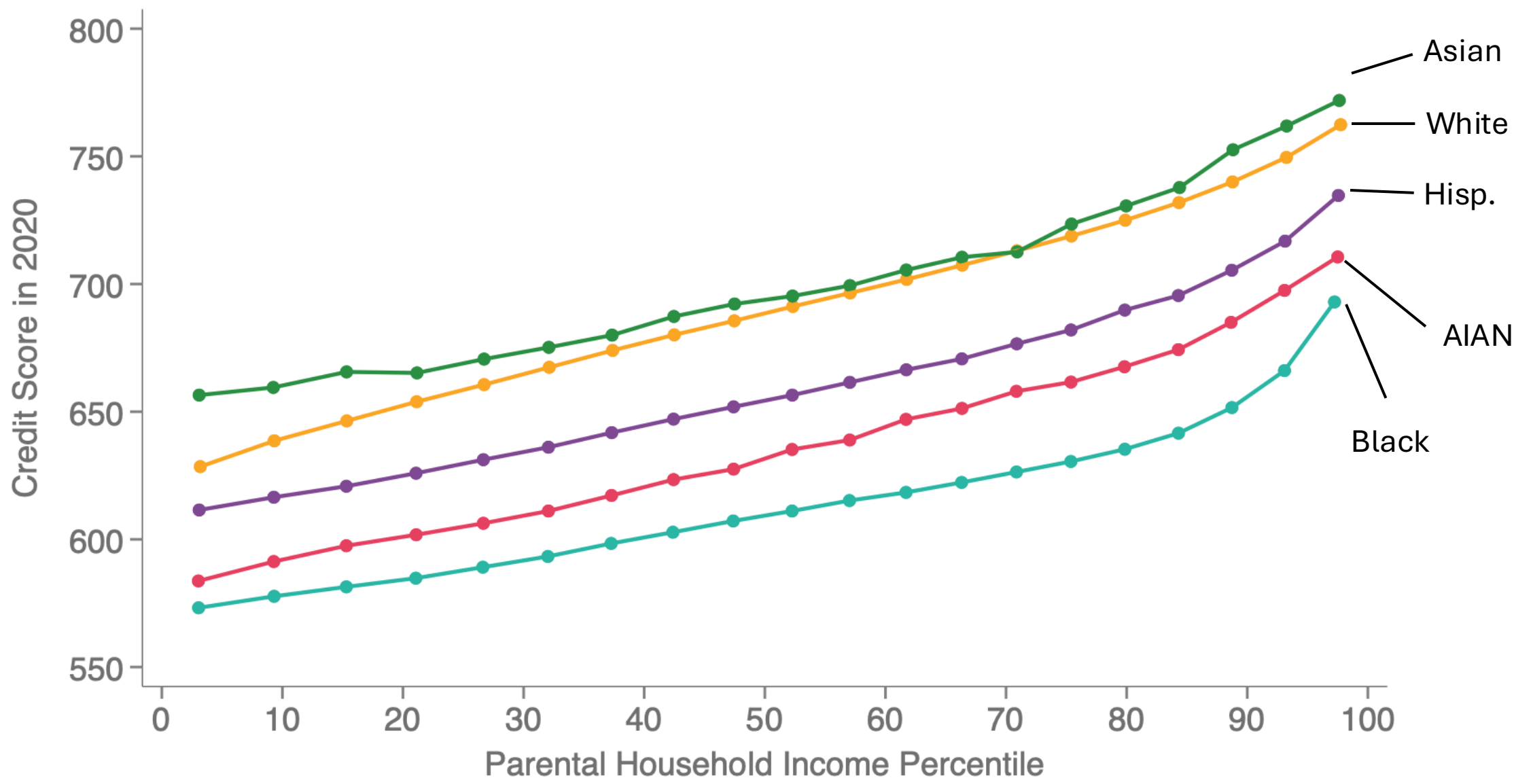
Credit Scores by Race and Parental Income 2020



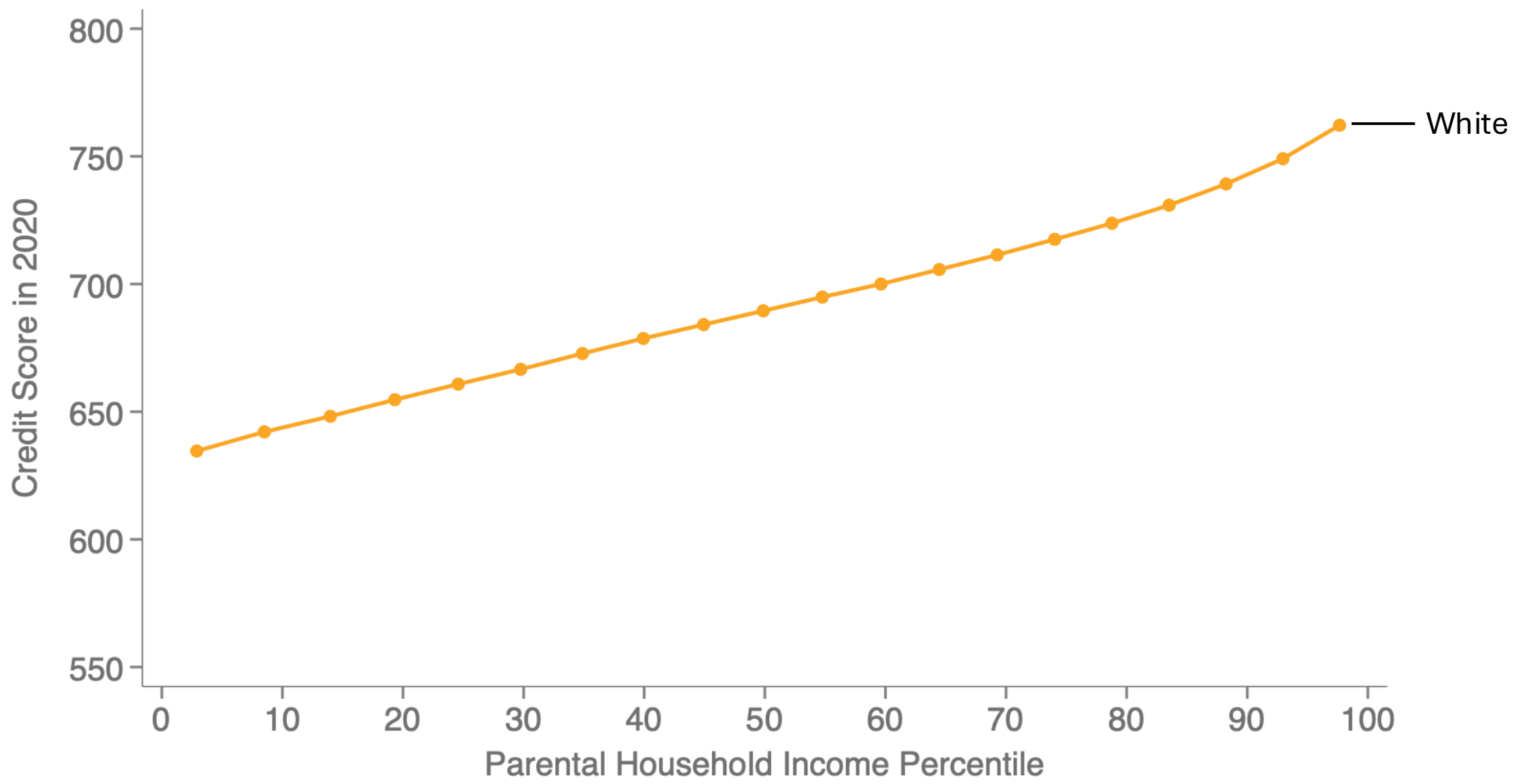
Credit Scores by Race and Parental Income 2020



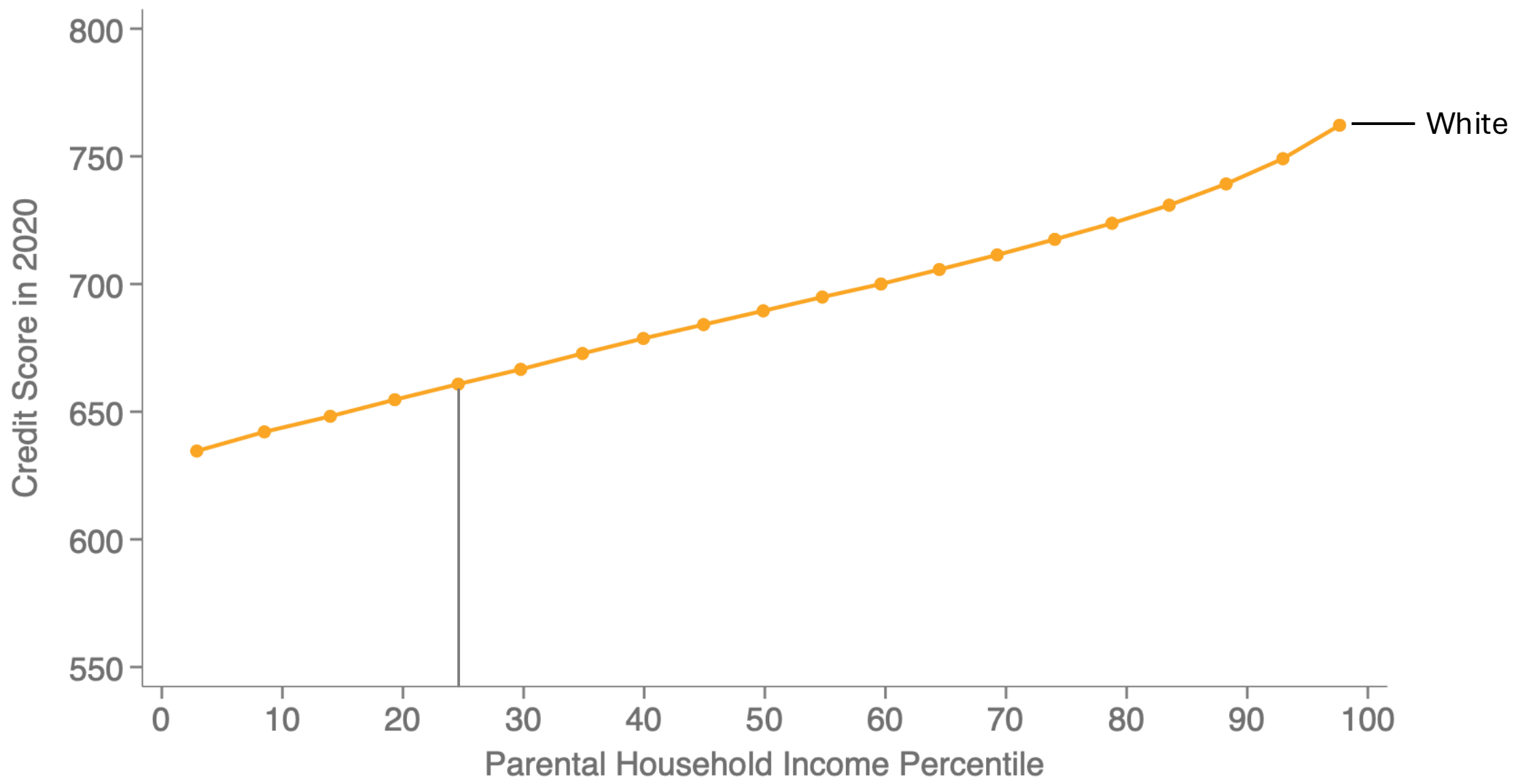
Credit Scores by Race and Parental Income 2020, Native-born Mothers



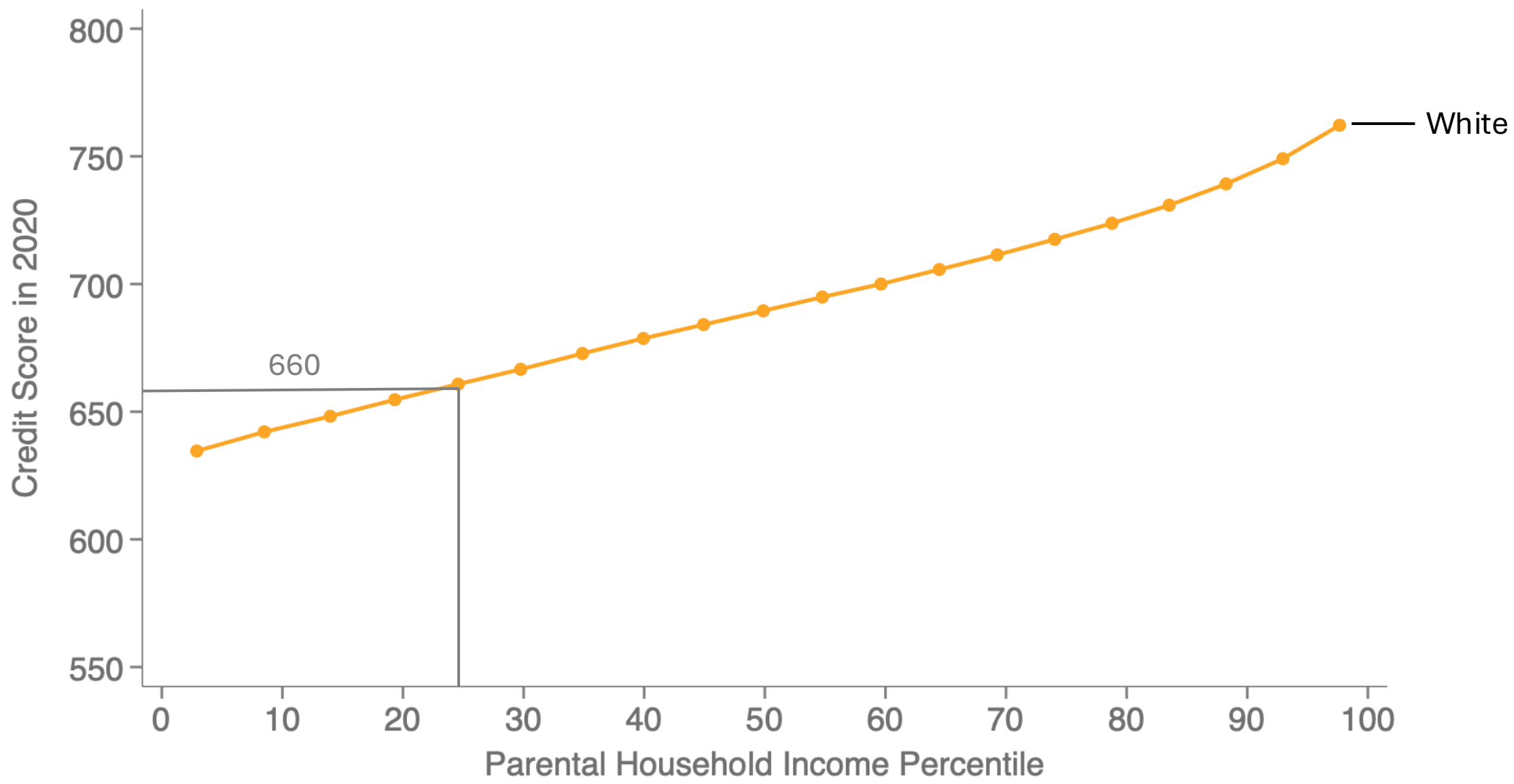
Credit Scores by Race and Parental Income 2020



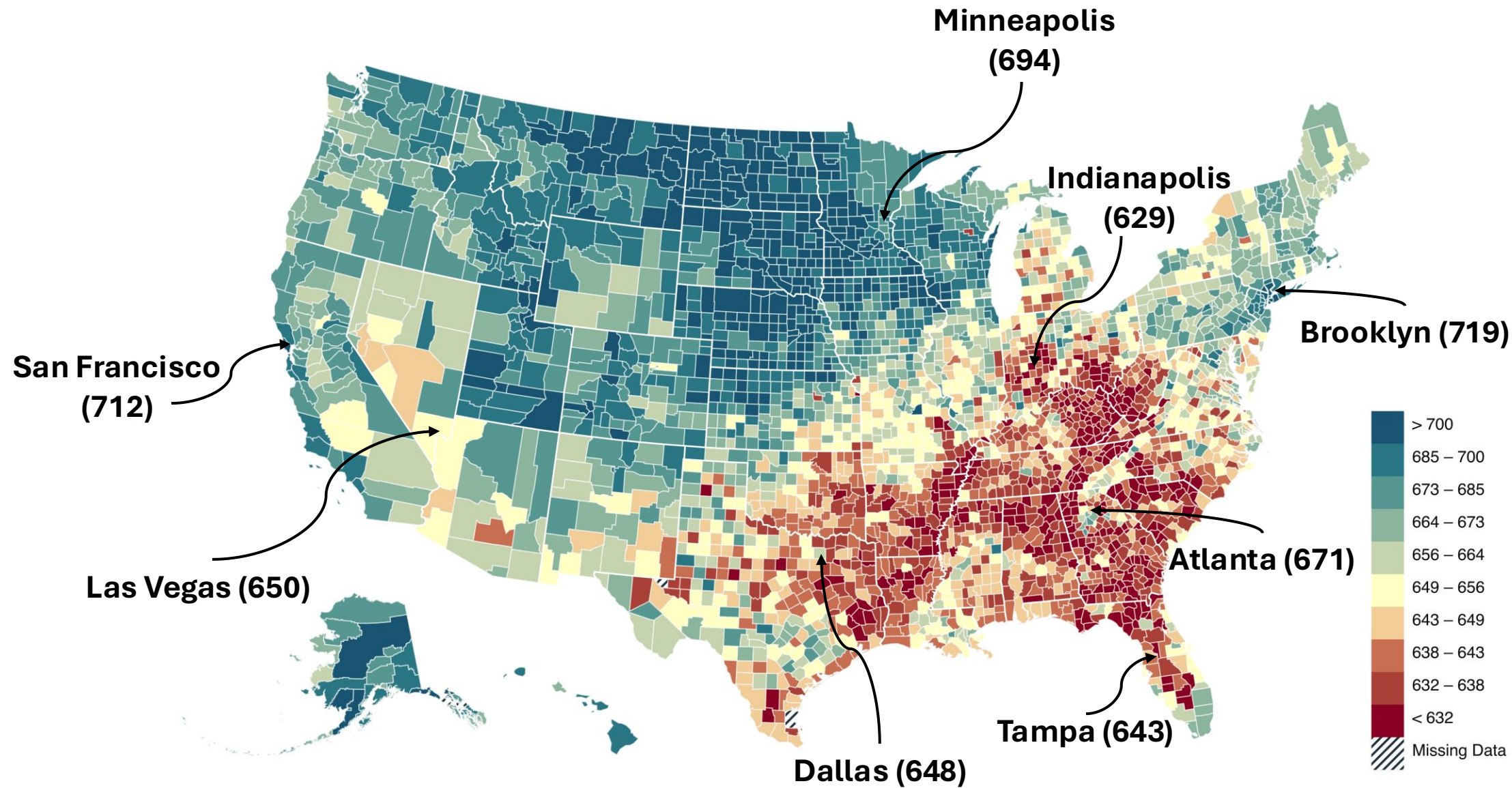
Credit Scores by Race and Parental Income 2020



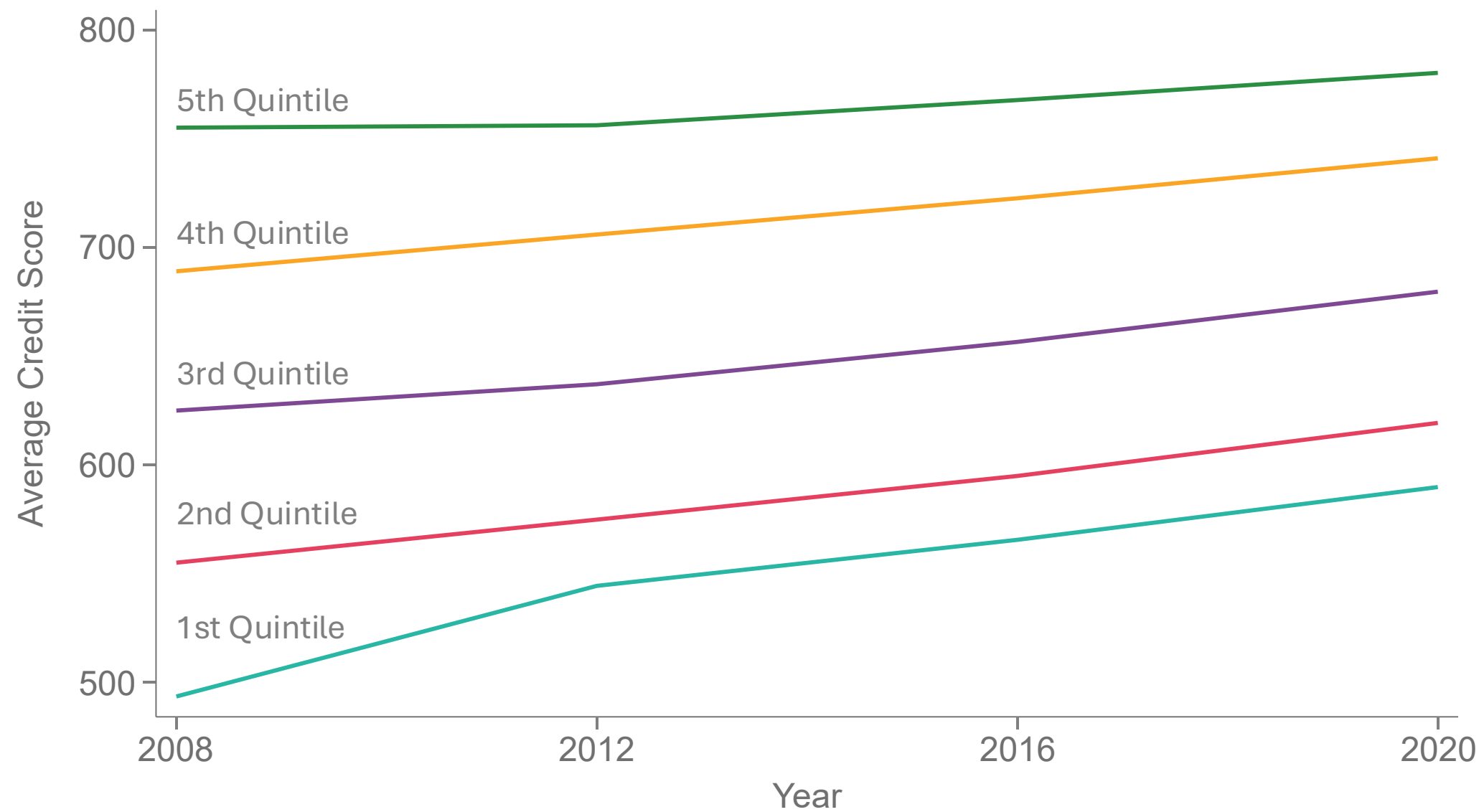
Credit Scores by Race and Parental Income 2020



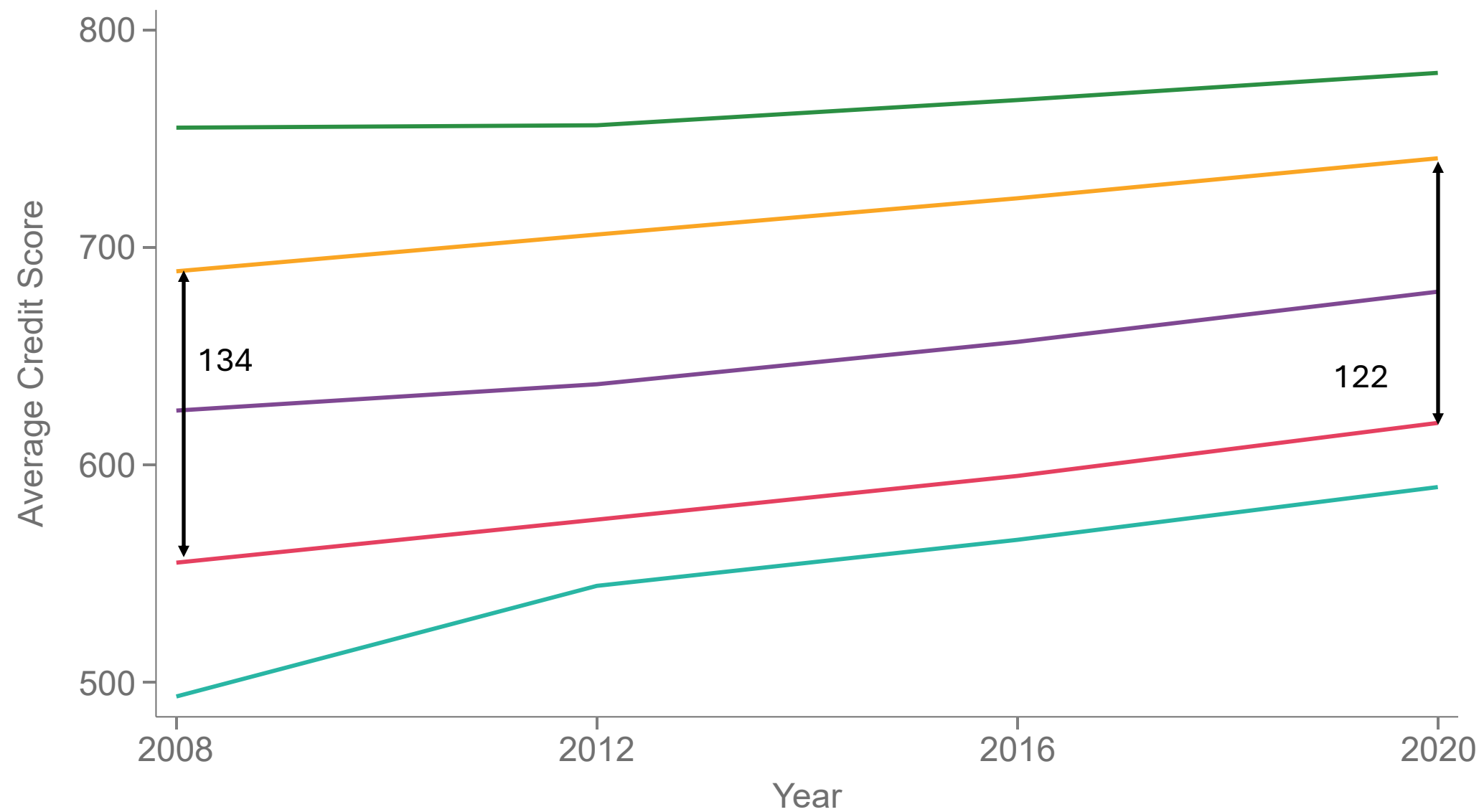
Credit Scores by County for White Individuals From Low-Income (p25) Families



Within-Person Persistence of Credit Scores



Within-Person Persistence of Credit Scores



Credit Scores versus Credit Constraints

Does the credit score capture differences in credit access?

Groups with lower credit scores have:

1. Lower balances [[link](#)]
2. More formal credit inquiries [[link](#)]
3. Higher relative share of student loans [[link](#)]
4. Higher credit card utilization [[link](#)]
5. Lower ability to get \$2,000 to cover an unexpected need ([Nat'l Fin. Capability Study](#))
6. More likely to rely on alternative credit [[link](#)]

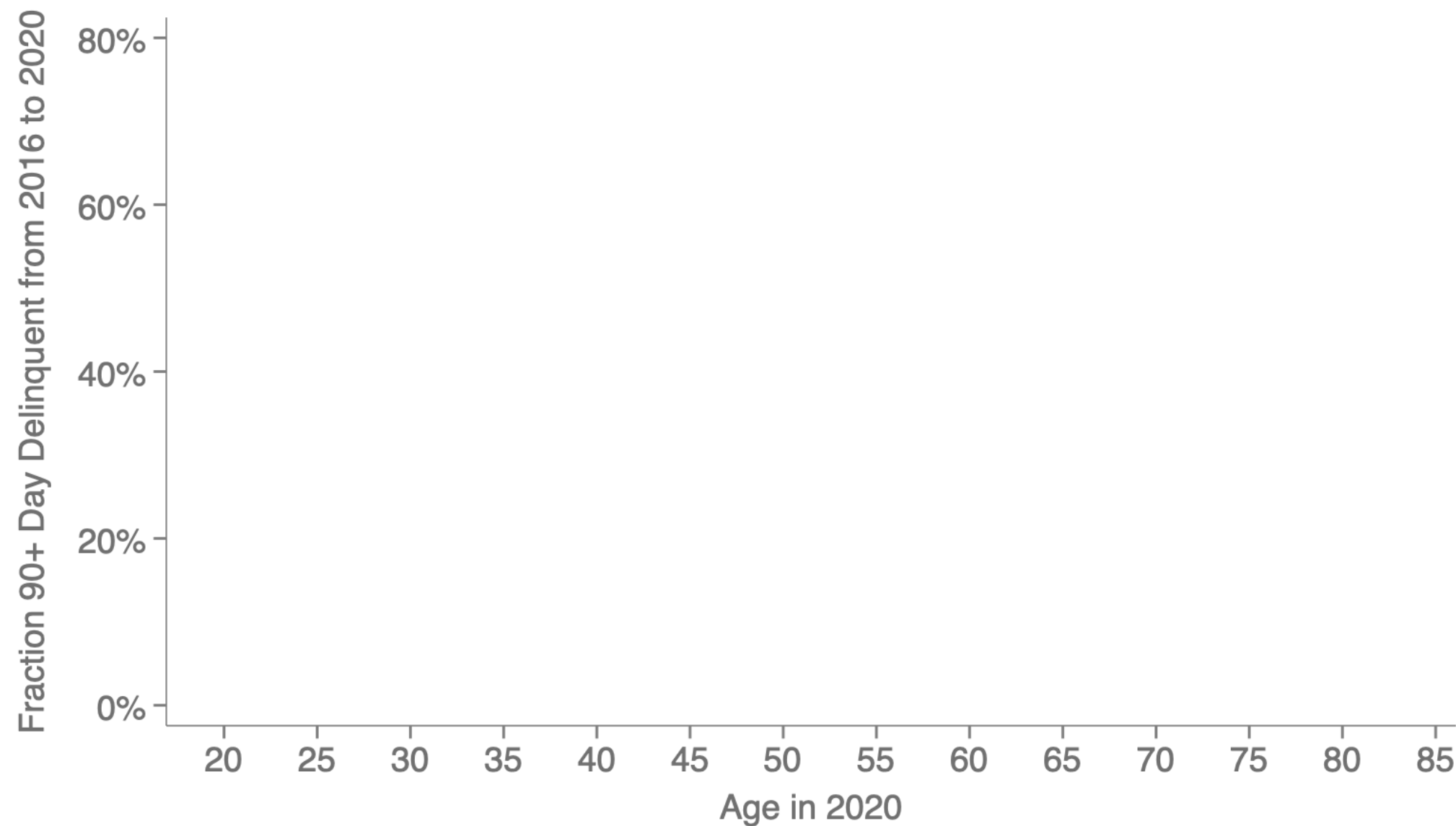
Conclude that groups with lower credit scores face greater credit constraints

What Drives Differences in Credit Scores/Access? The Role of Non-Repayment

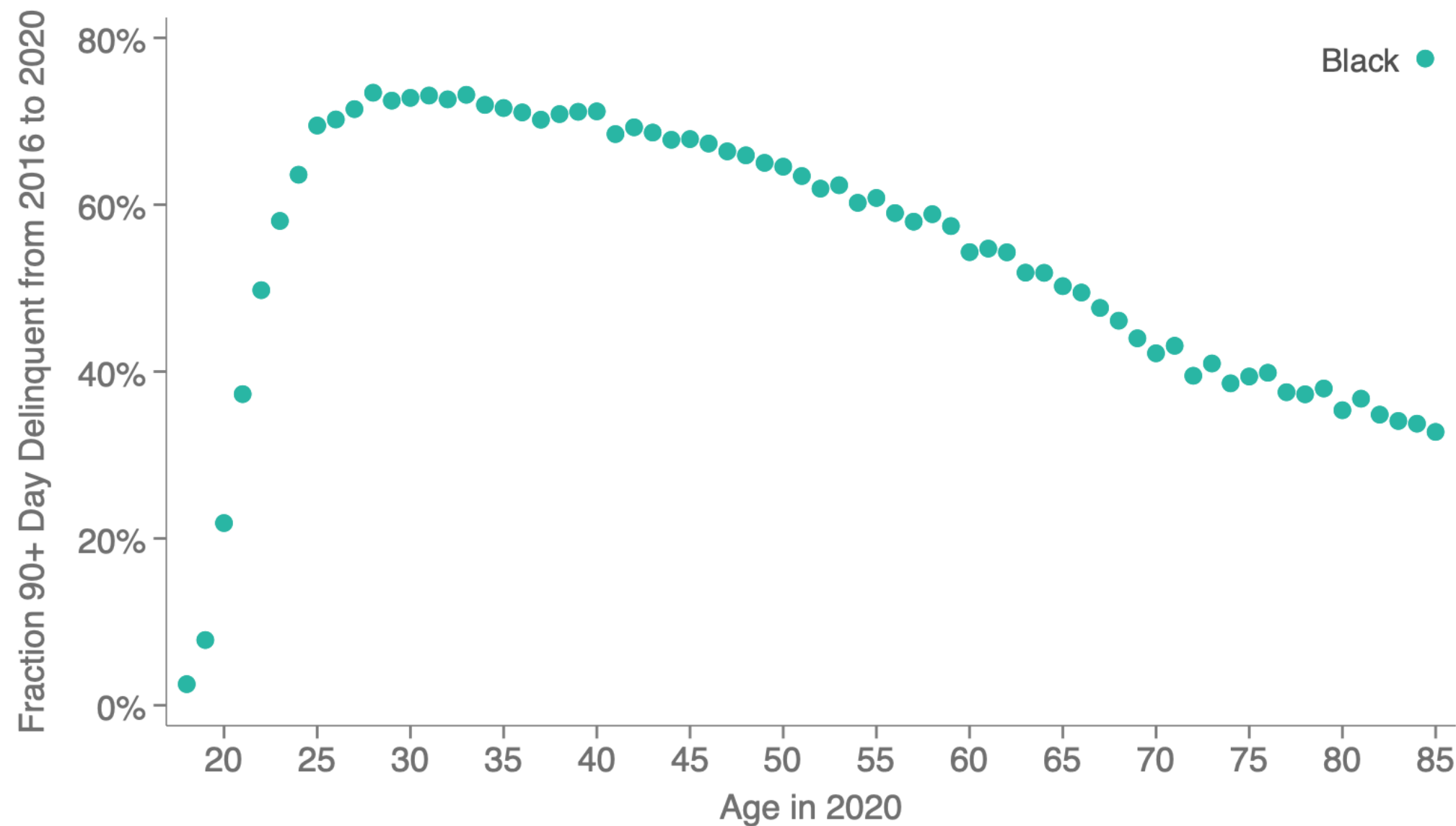
- Natural reason to restrict credit is that the lender is afraid they won't be repaid
- Credit scores (Vantage and FICO) seek to predict future 90+ day delinquency, with the idea this prediction is helpful for measuring creditworthiness
- Measure rate of 90+ day delinquency by group



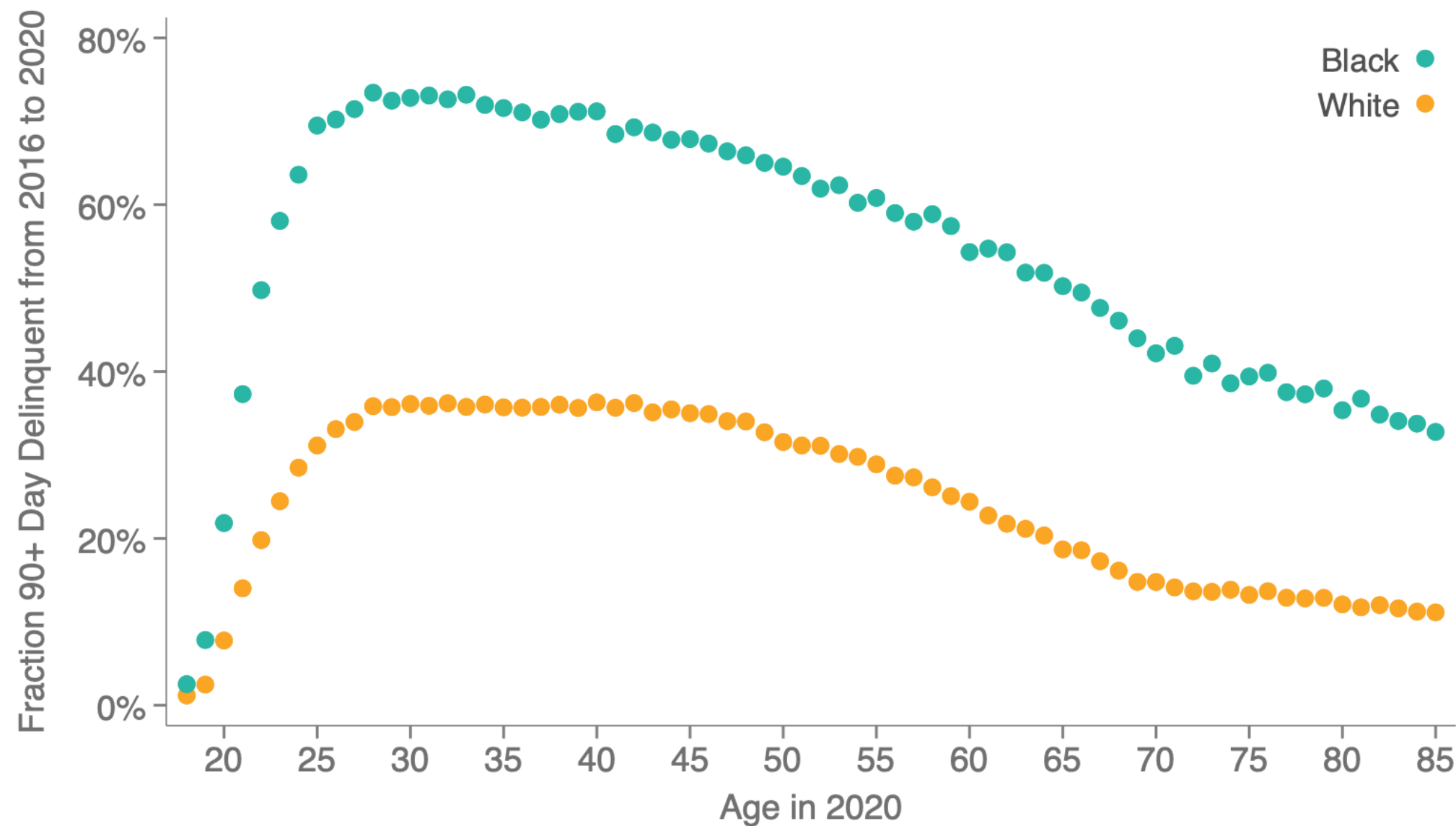
Presence of Late Payment on Credit Report by Age and Race (90+ day)



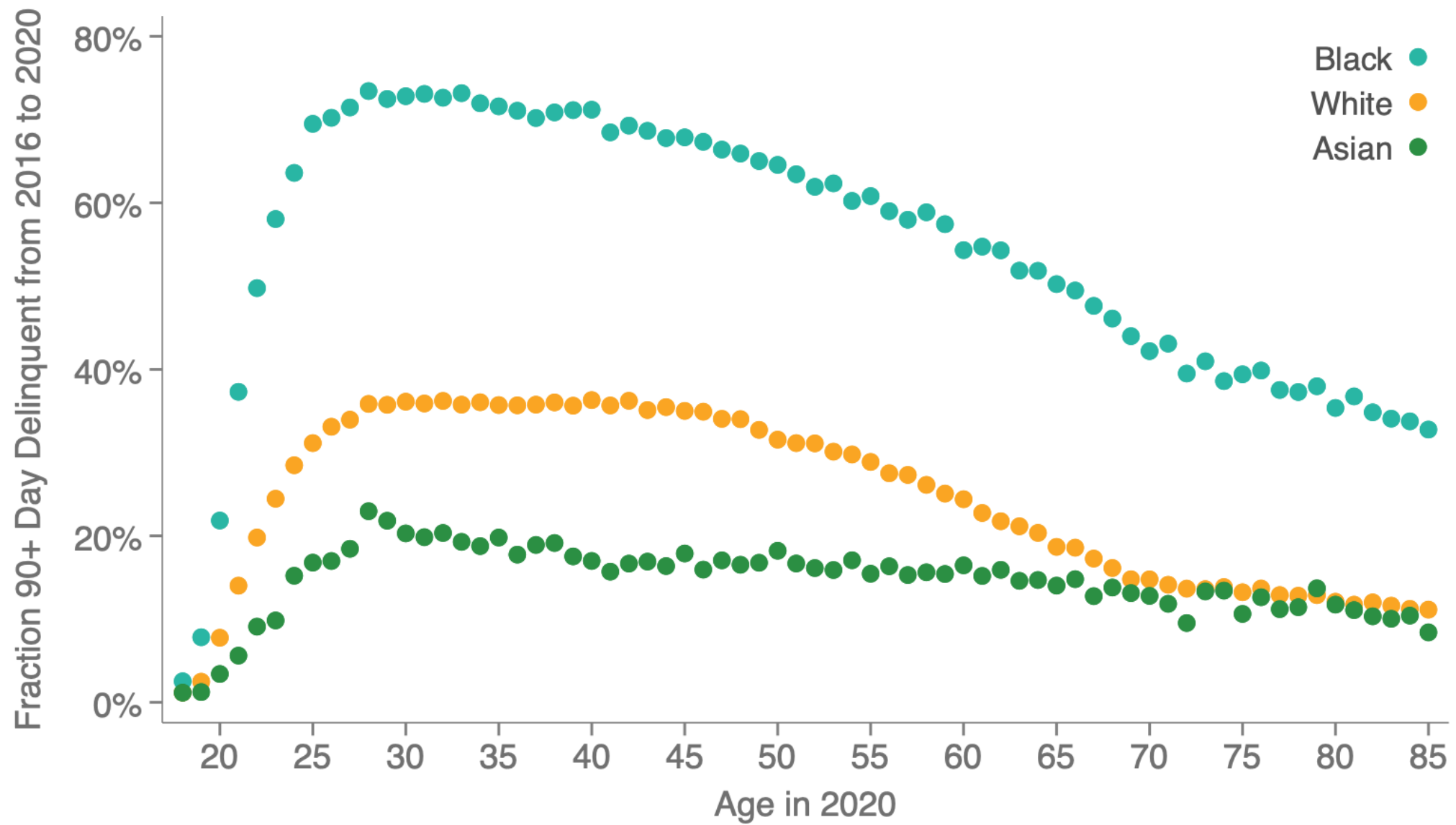
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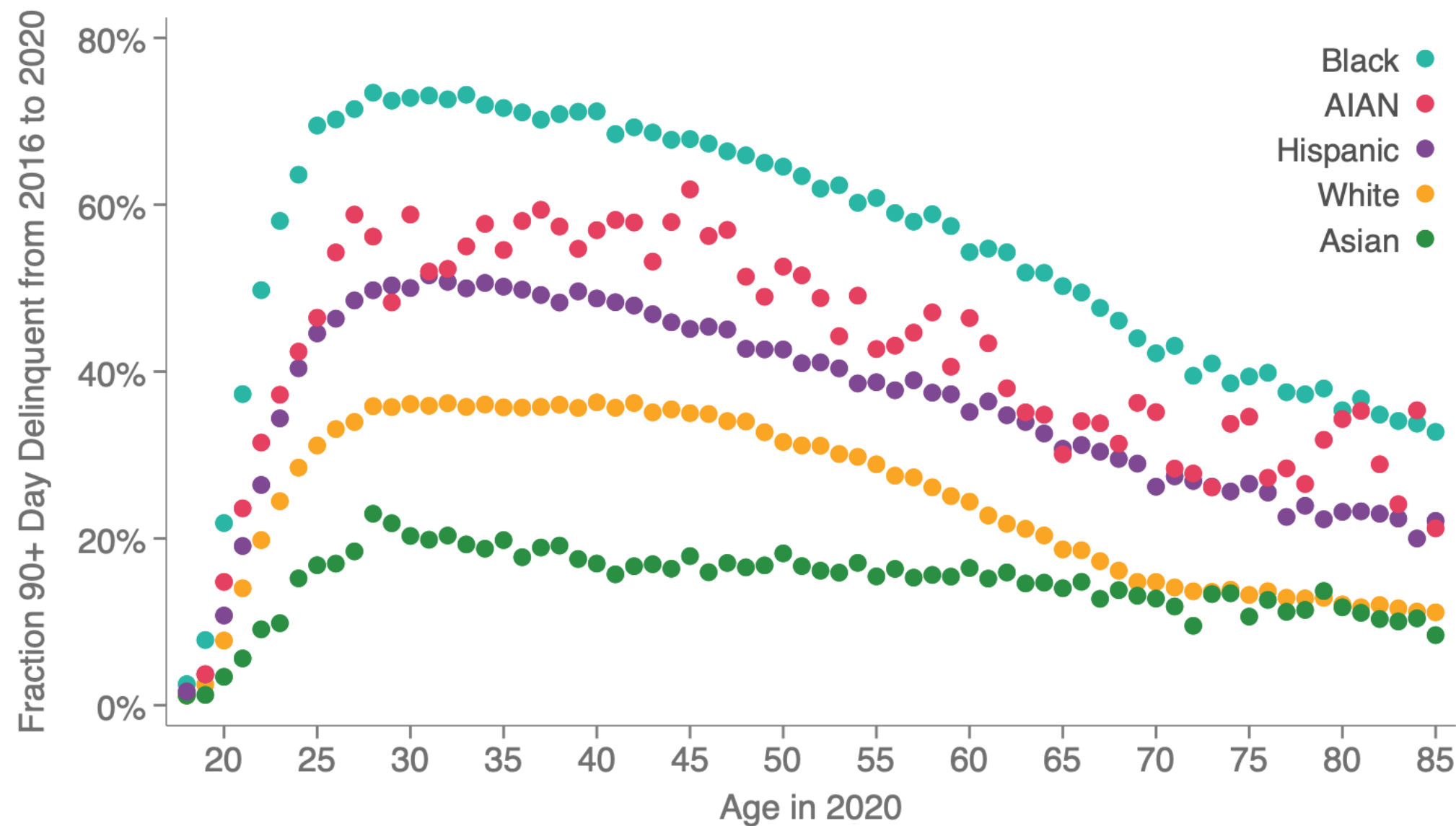
Presence of Late Payment on Credit Report by Age and Race (90+ day)



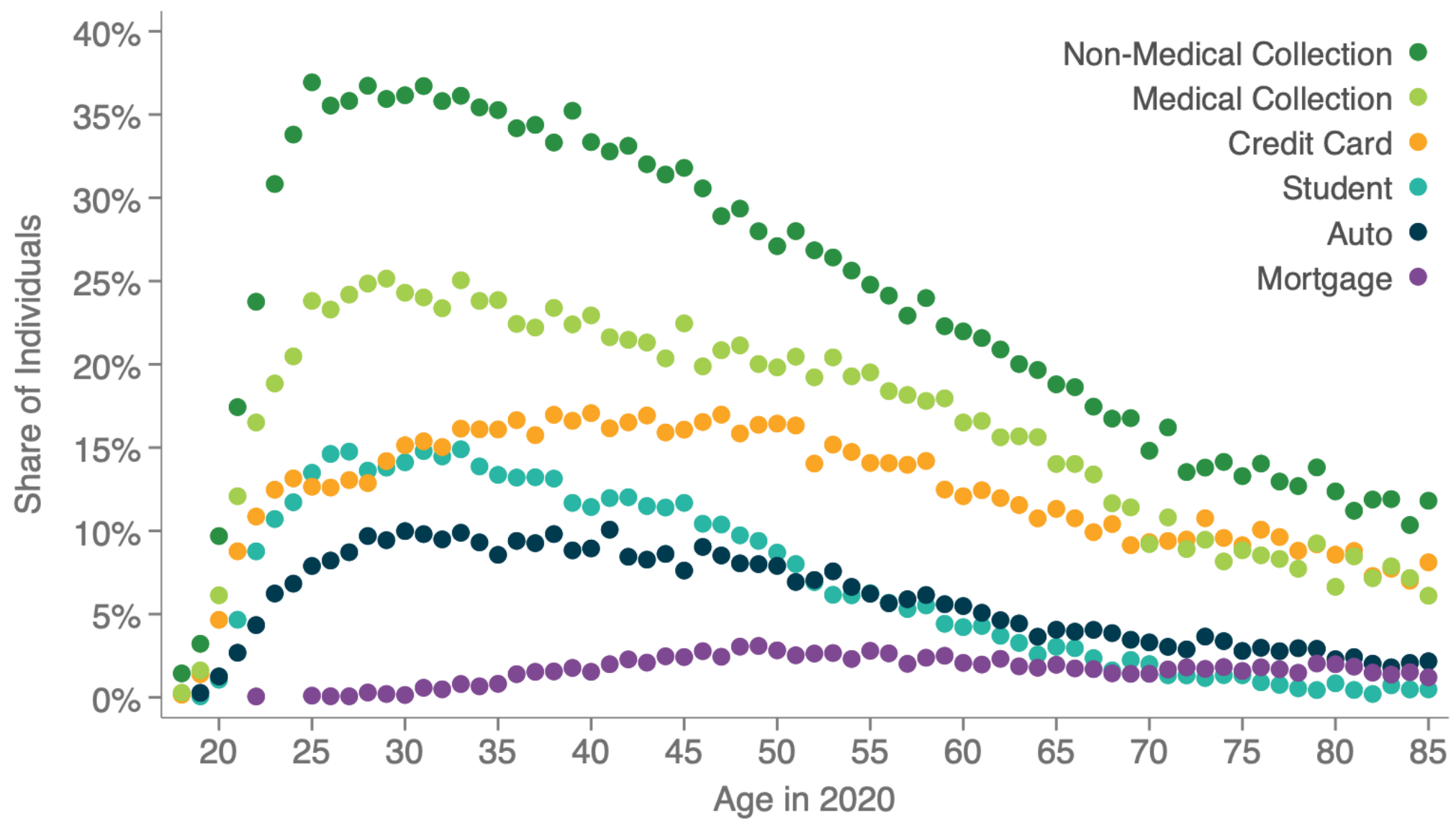
Presence of Late Payment on Credit Report by Age and Race (90+ day)



Presence of Late Payment on Credit Report by Age and Race (90+ day)



90+ Day Late Payment Breakdown for Black Individuals

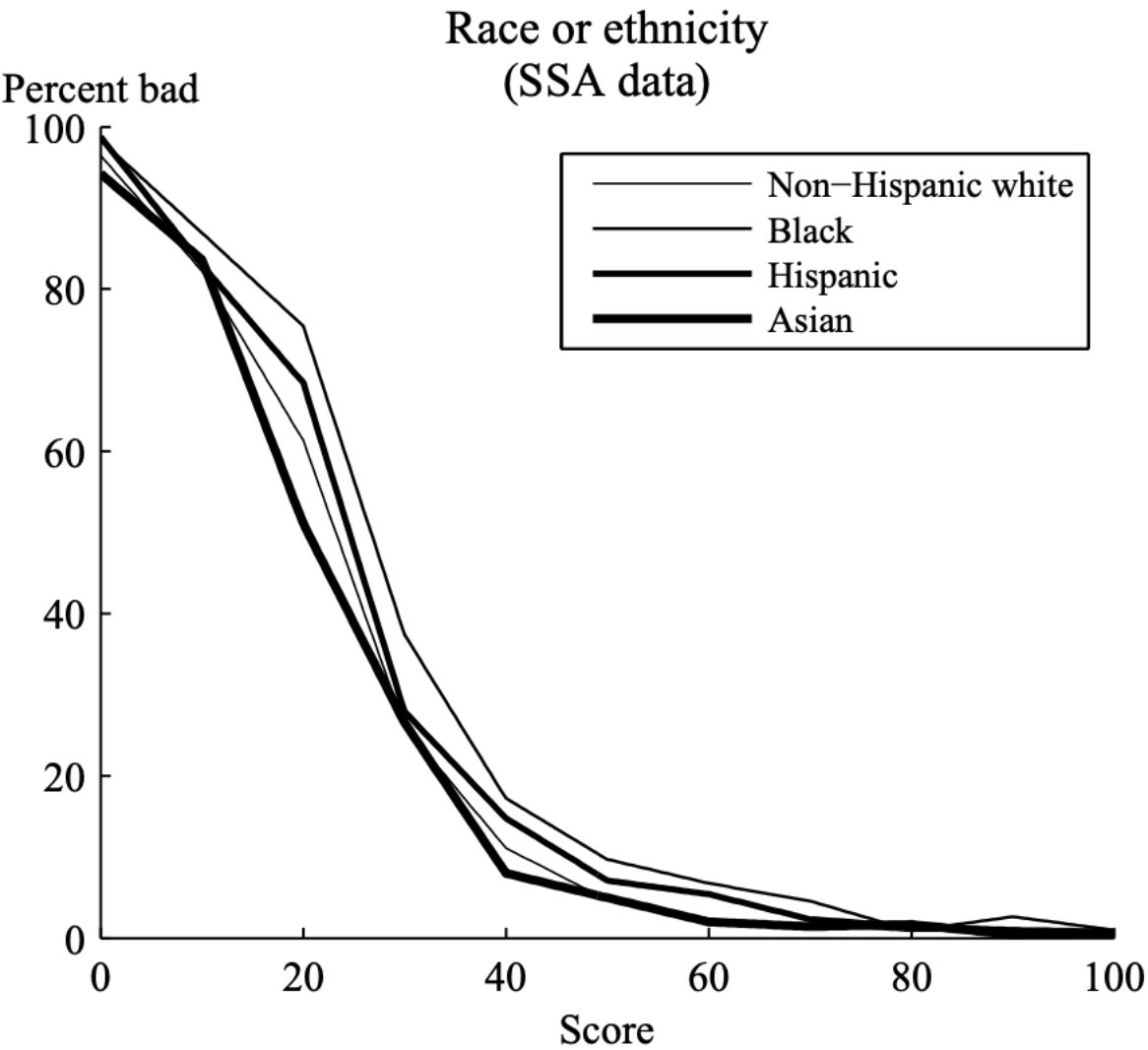


Algorithmic Bias in Credit Scores

- Large gaps in credit scores and repayment by race, class, and hometown
- Are the differences in credit scores accurate reflections of these non-repayment differences or is there algorithmic bias? [e.g. Fuster et al. (2022); Blattner and Nelson (2024); Elzayn et al. (2025); Arnold et al. (2025)]
- Assess relationship between credit scores and future delinquencies to evaluate algorithmic bias of the credit score
 - Caveat: May differ from bias in firm decisions using the algorithm
- **Calibration Bias:** Are there disparities in future 90+ day delinquency conditional on the credit score?

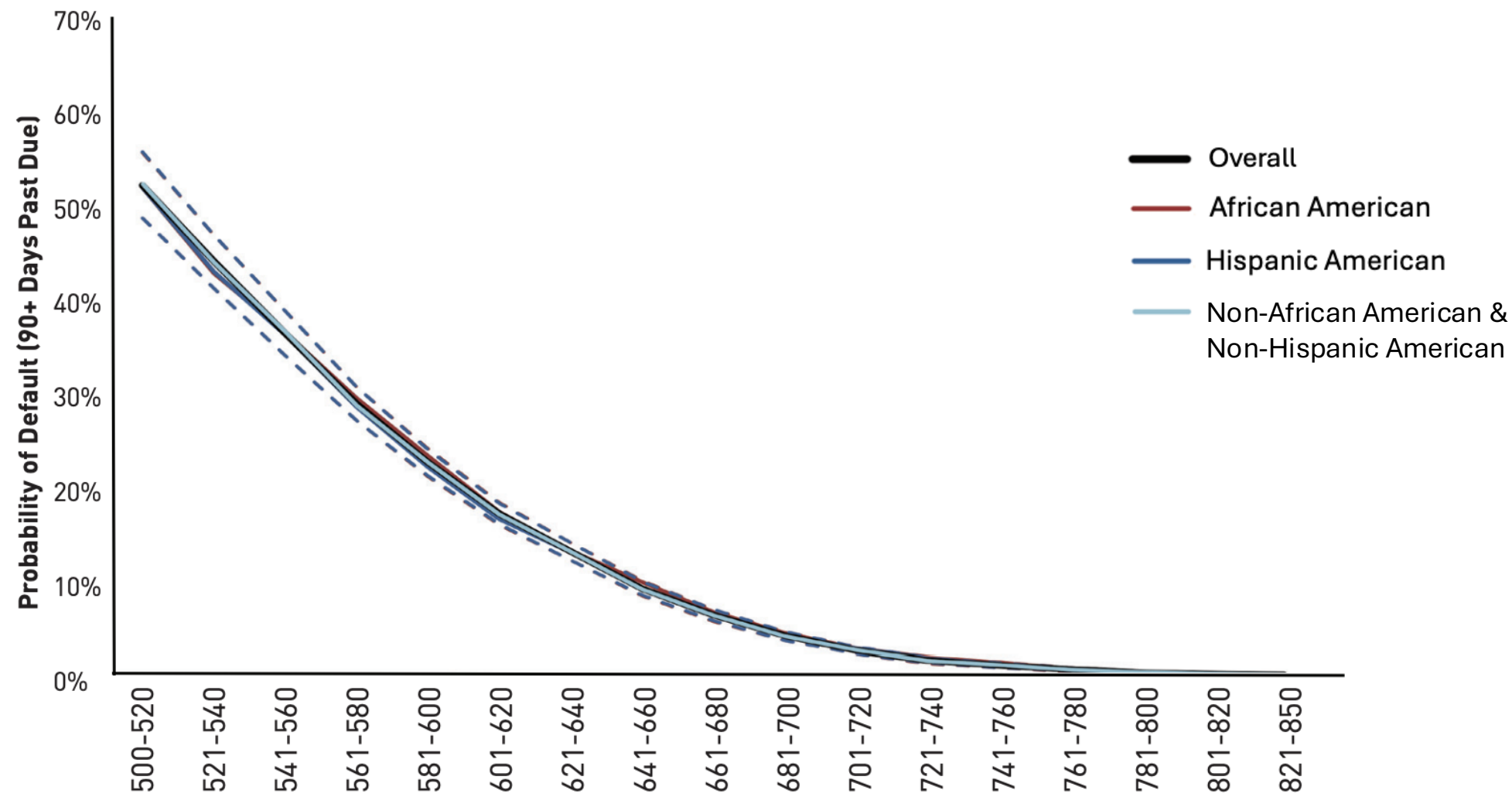


2003 Fed Board Analysis Finds Calibration Bias of Credit Score Against White Borrowers [Federal Reserve Board (2007); Avery, Brevoort, and Canner (2009)]

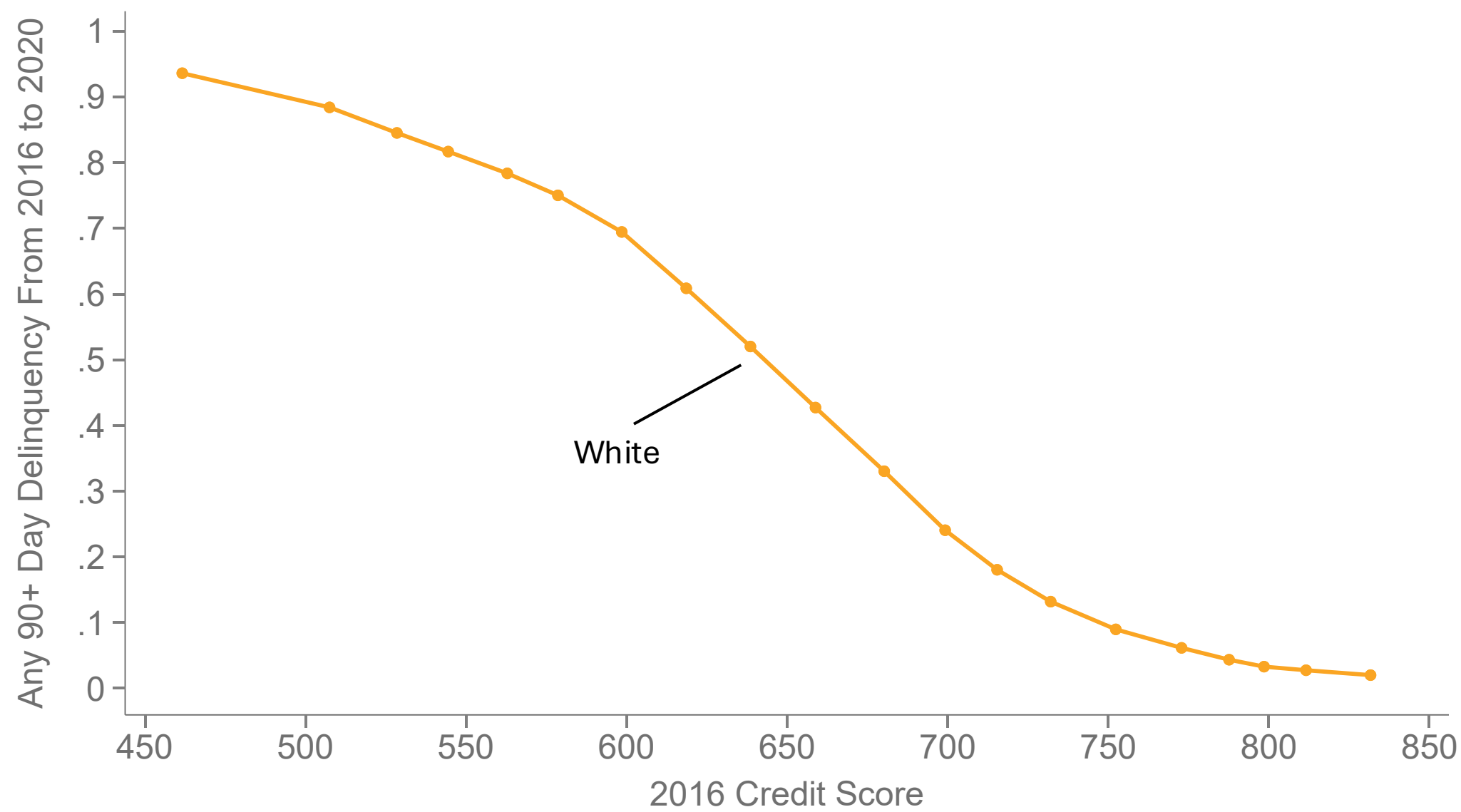


But Vantage 4.0 Argues No Calibration Bias Today (Zipcode imputation)

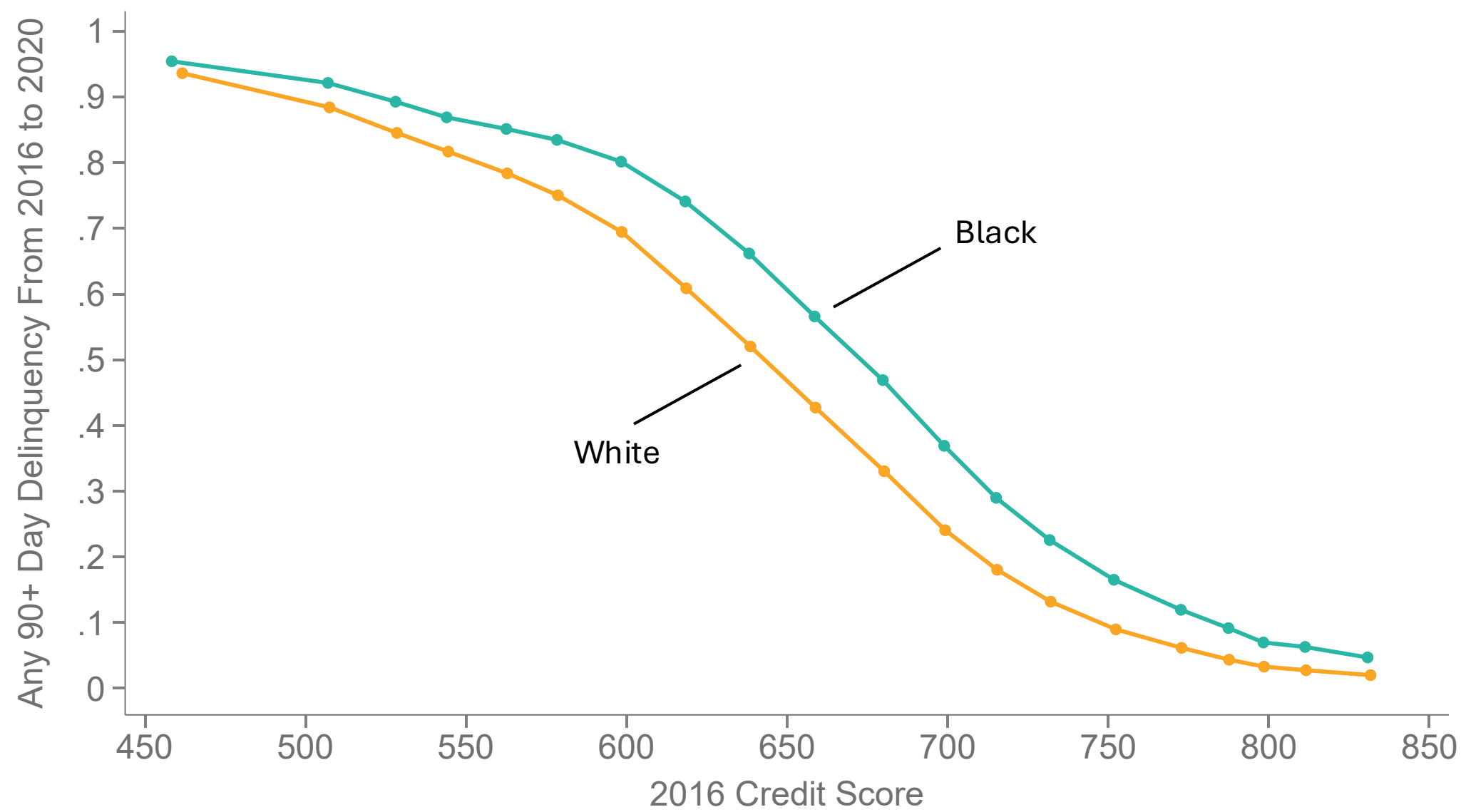
Figure 22: Statistical Bias: Bankcard default profiles by ethnicity with confidence intervals



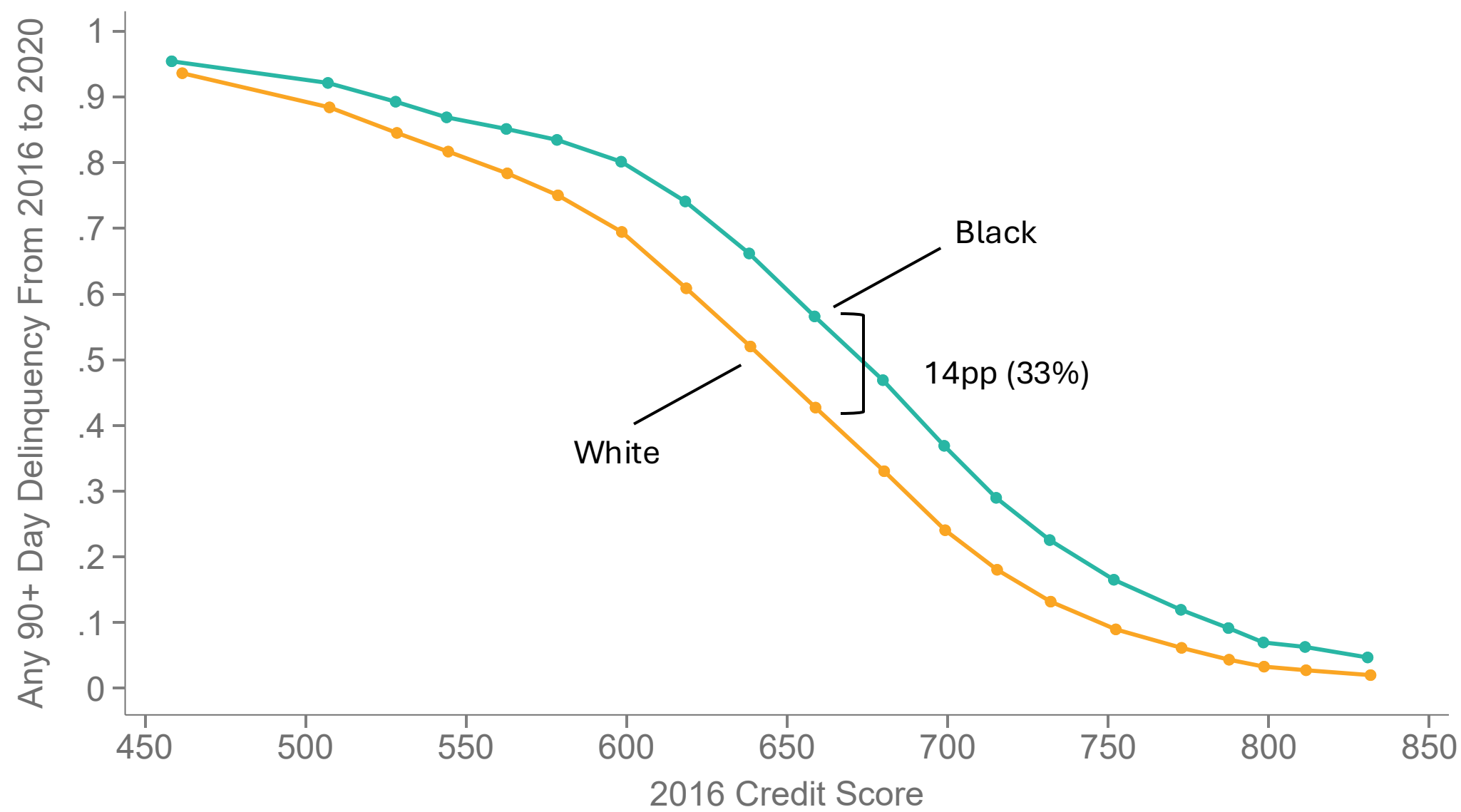
Racial Calibration: Credit Scores are Predictive of Future Delinquency



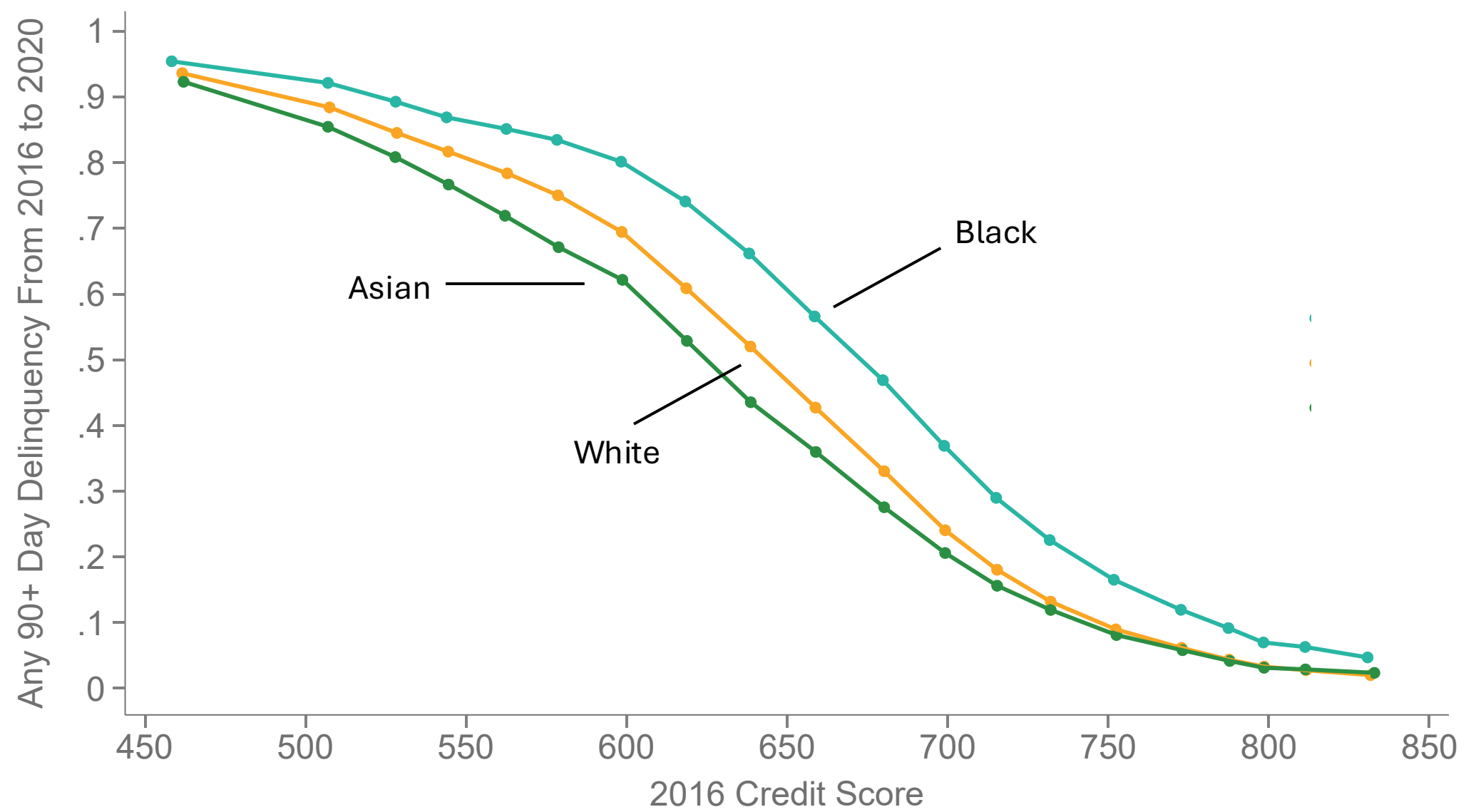
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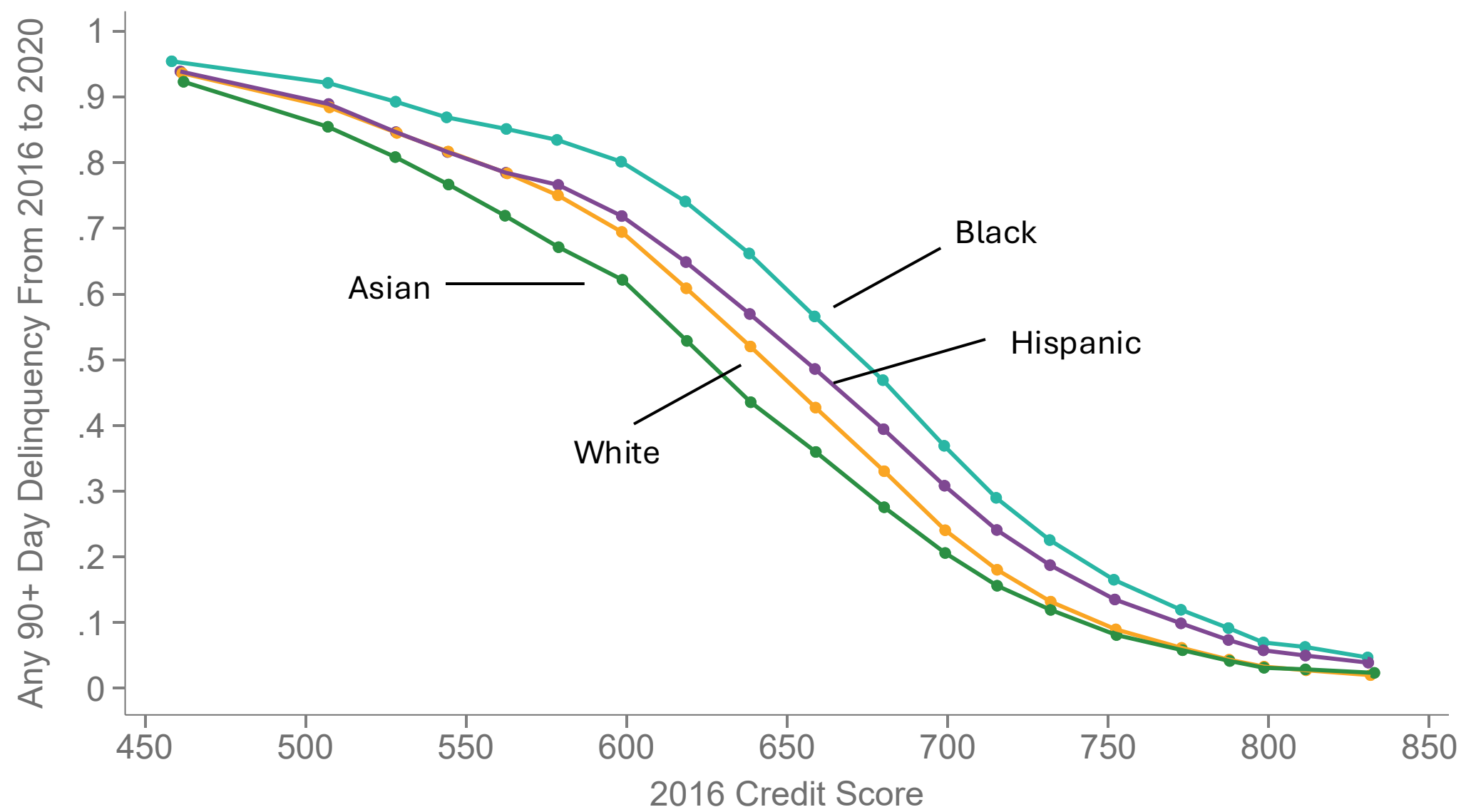
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Summary of Measurement of Credit Access

- Large differences in credit scores by race, class, and hometown, that emerge early in the life cycle
- Credit score gaps align with and even understate differences in delinquency rates across groups
- **Key Question:** What drives the large group-level differences in repayment that emerge early in the life cycle?

What Drives Differences in Repayment by Race, Class, and Hometown?

Two theories:

1. Differences in adult incomes/wealth
 - Large differences in income/wealth by race, class, and hometown
2. Differences in childhood environments
 - Gaps emerge early in life cycle and we know incomes are driven by childhood exposure to neighborhoods

Economic model of repayment: $r_i = m(y_i, c_i, \epsilon_i)$

- y_i is adult income / budget constraint
- c_i is childhood inputs (potentially correlated with y_i)
- ϵ_i are other determinants (e.g. random shocks)



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Assess these theories using two empirical strategies:

1. Observational controls for income
2. Causal strategy focused on hometown gaps to isolate childhood inputs and study mediation through income



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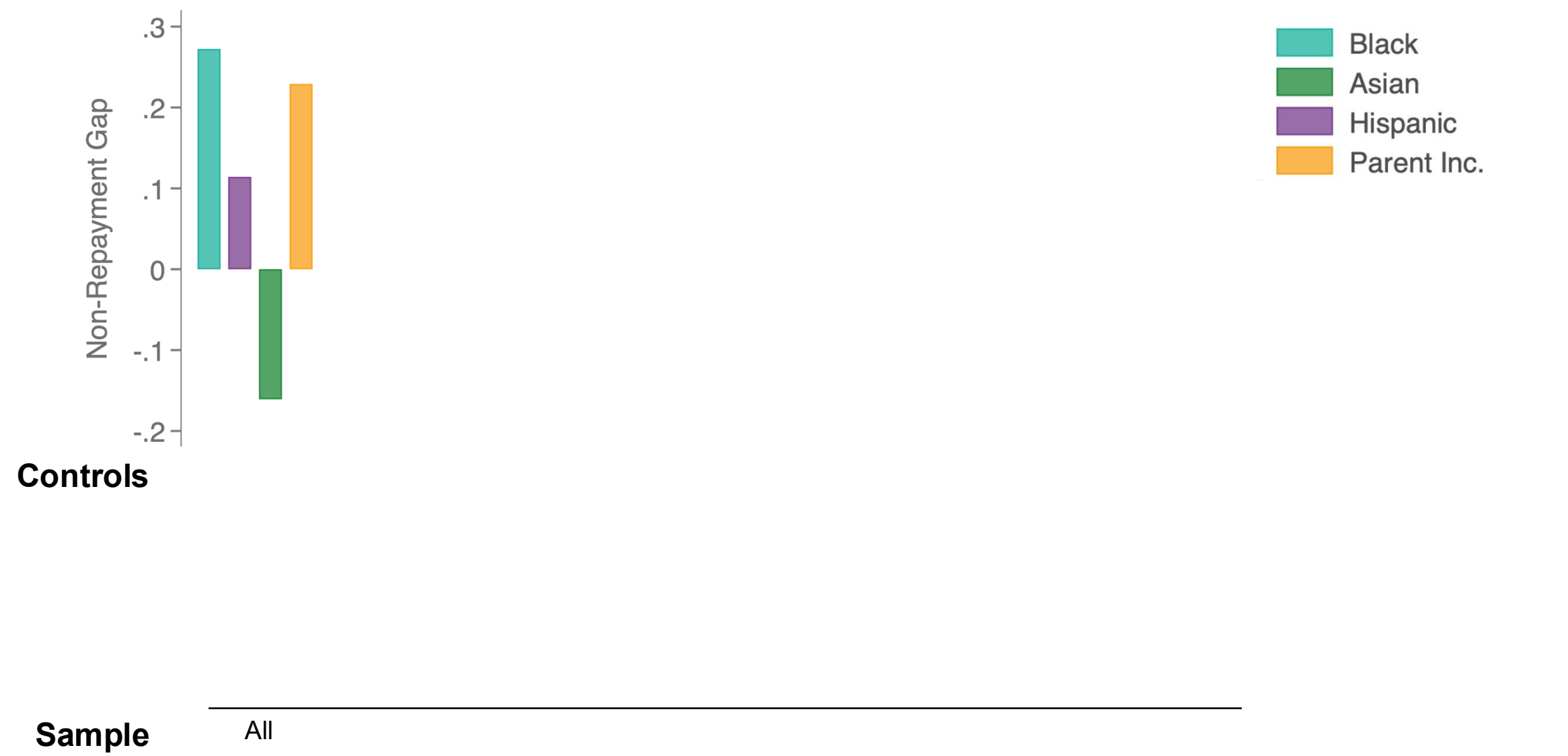
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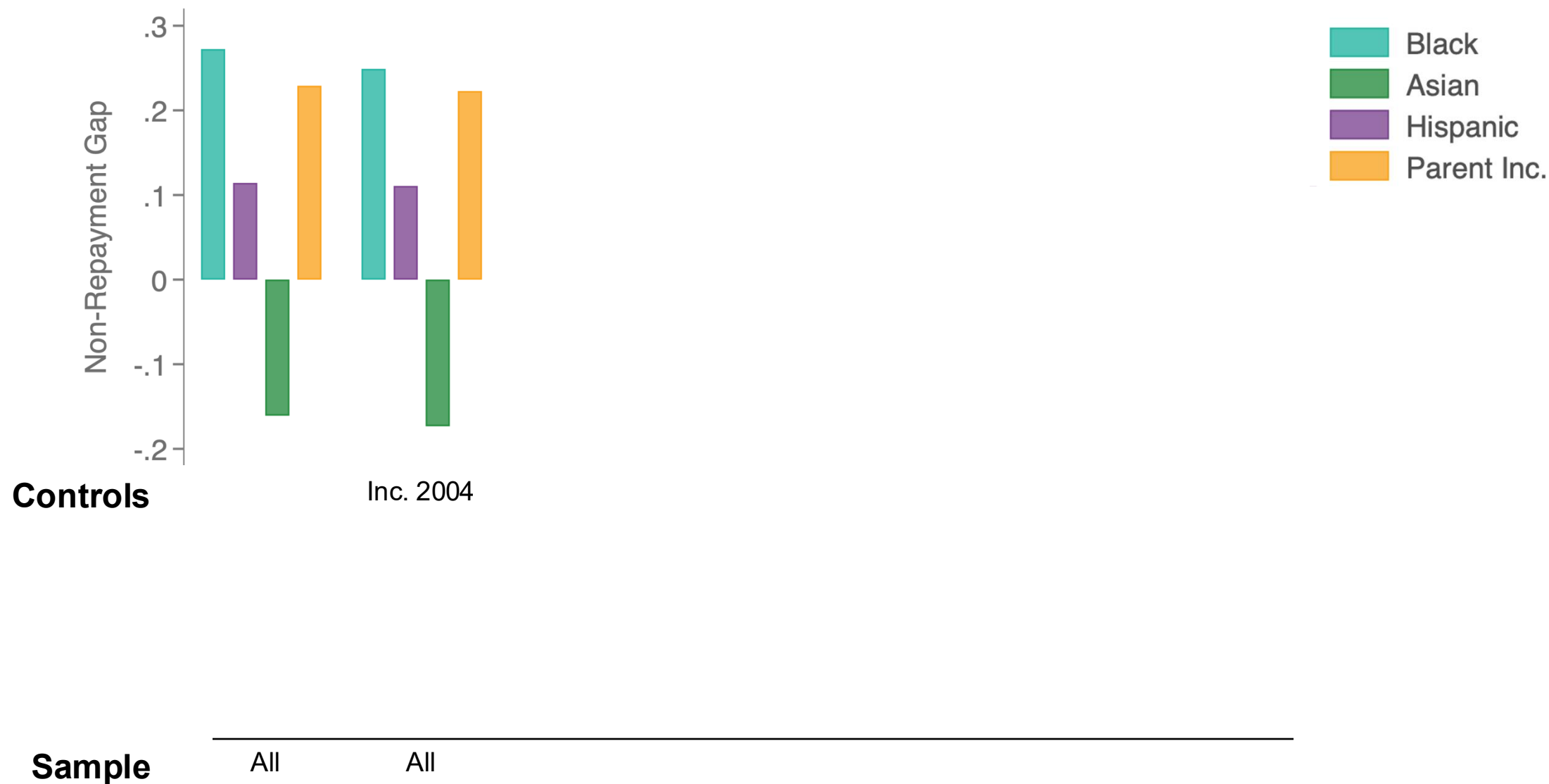
1. **Observational controls for income**
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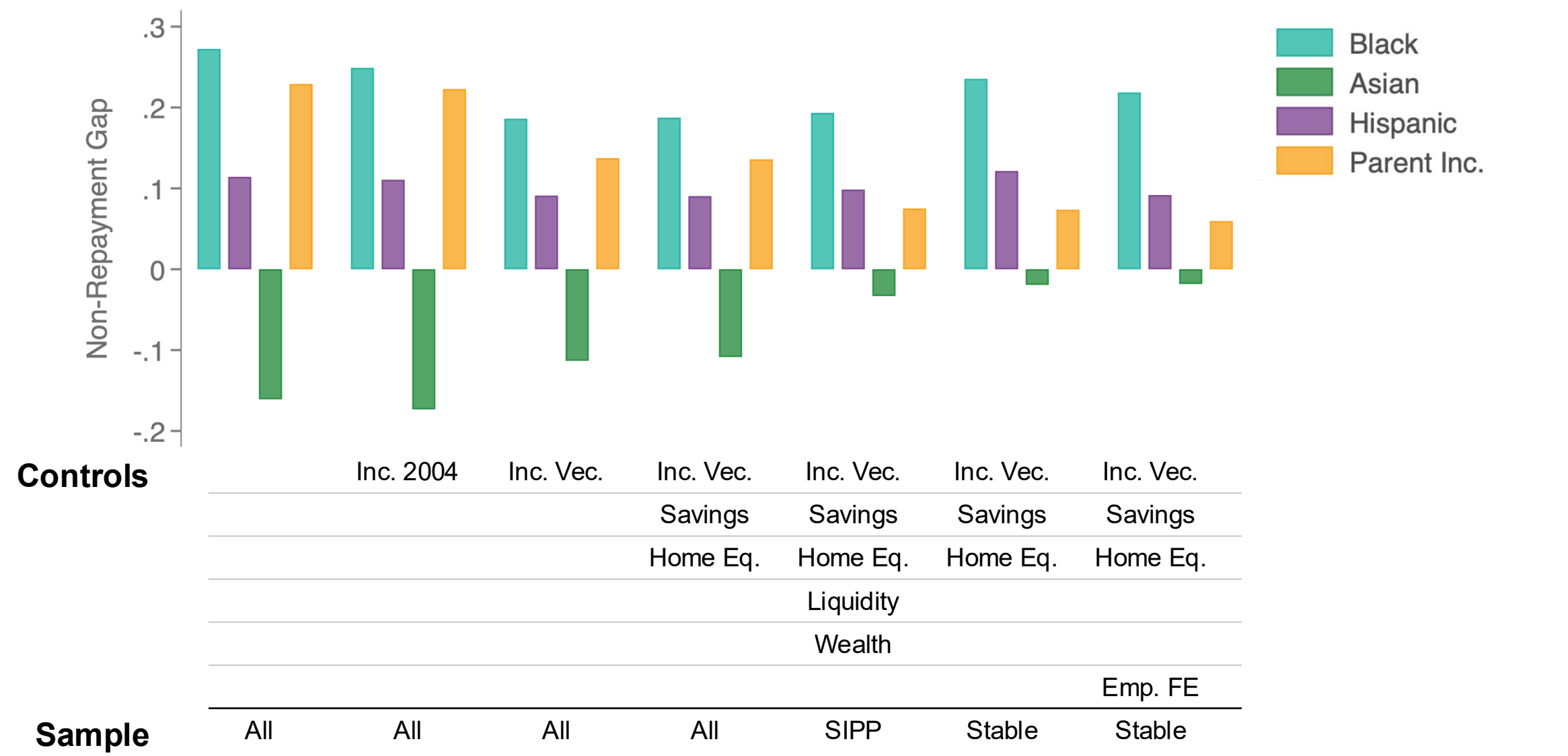
1. The Role of Income and Wealth in Explaining 90+ Day Delinquency (Age 24-30)



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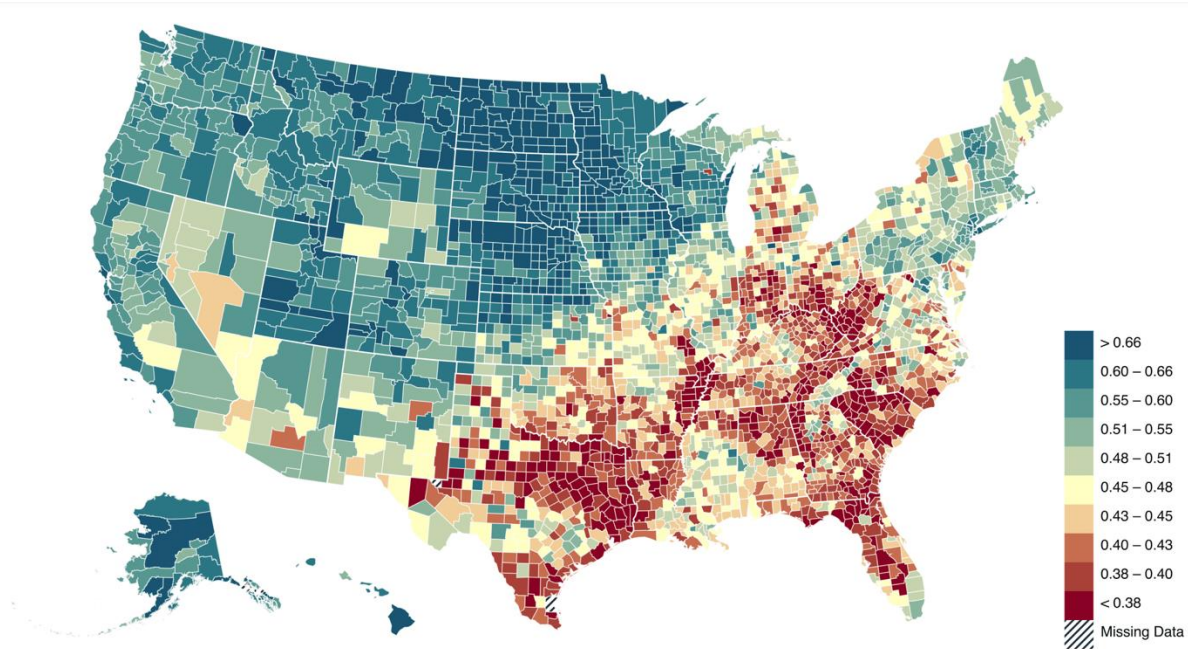


1. The Role of Income and Wealth in Explaining 90+ Day Delinquency (Age 24-30)

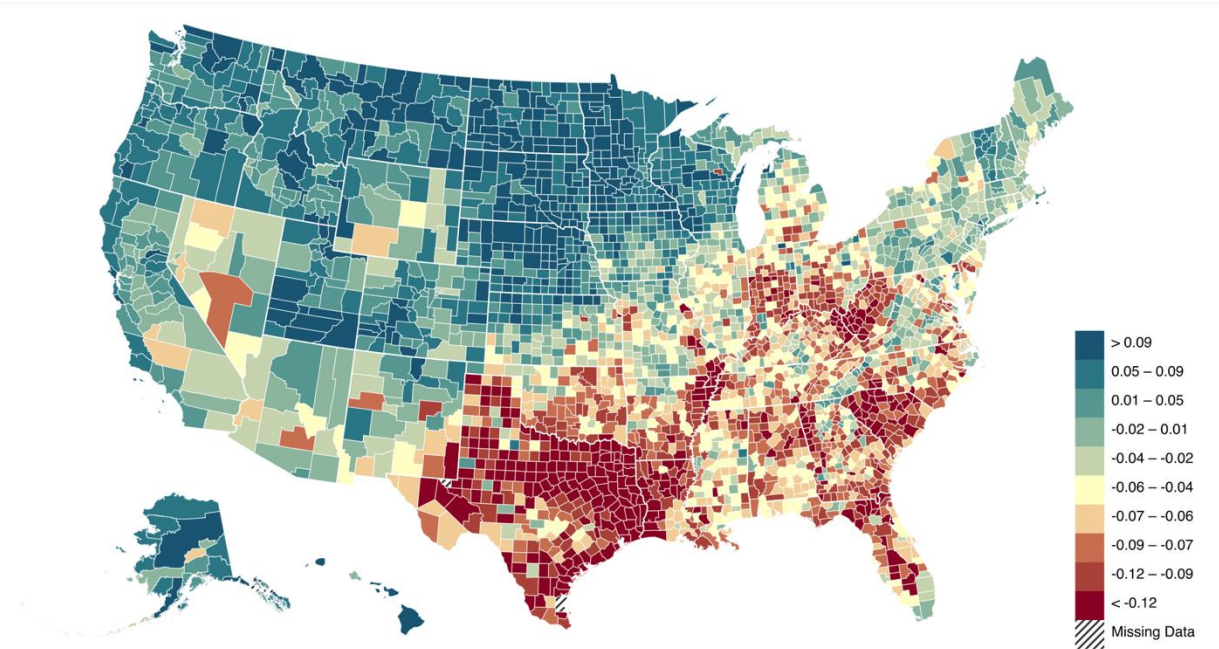


1. Repayment (No 90+ Day Delinquency) vs. Repayment Conditional on Income

White 25th Percentile Parental Income (2020)



Repayment



Repayment Conditional on Income

Role of Parental Credit Score in Explaining 90+ Day Delinquency in 2008

Intergenerational Sample

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

2. Causal Strategy to Identify Role of Childhood Inputs and Adult Income

Develop causal strategy to identify the impact of childhood inputs and understand the extent to which it is mediated through adult income

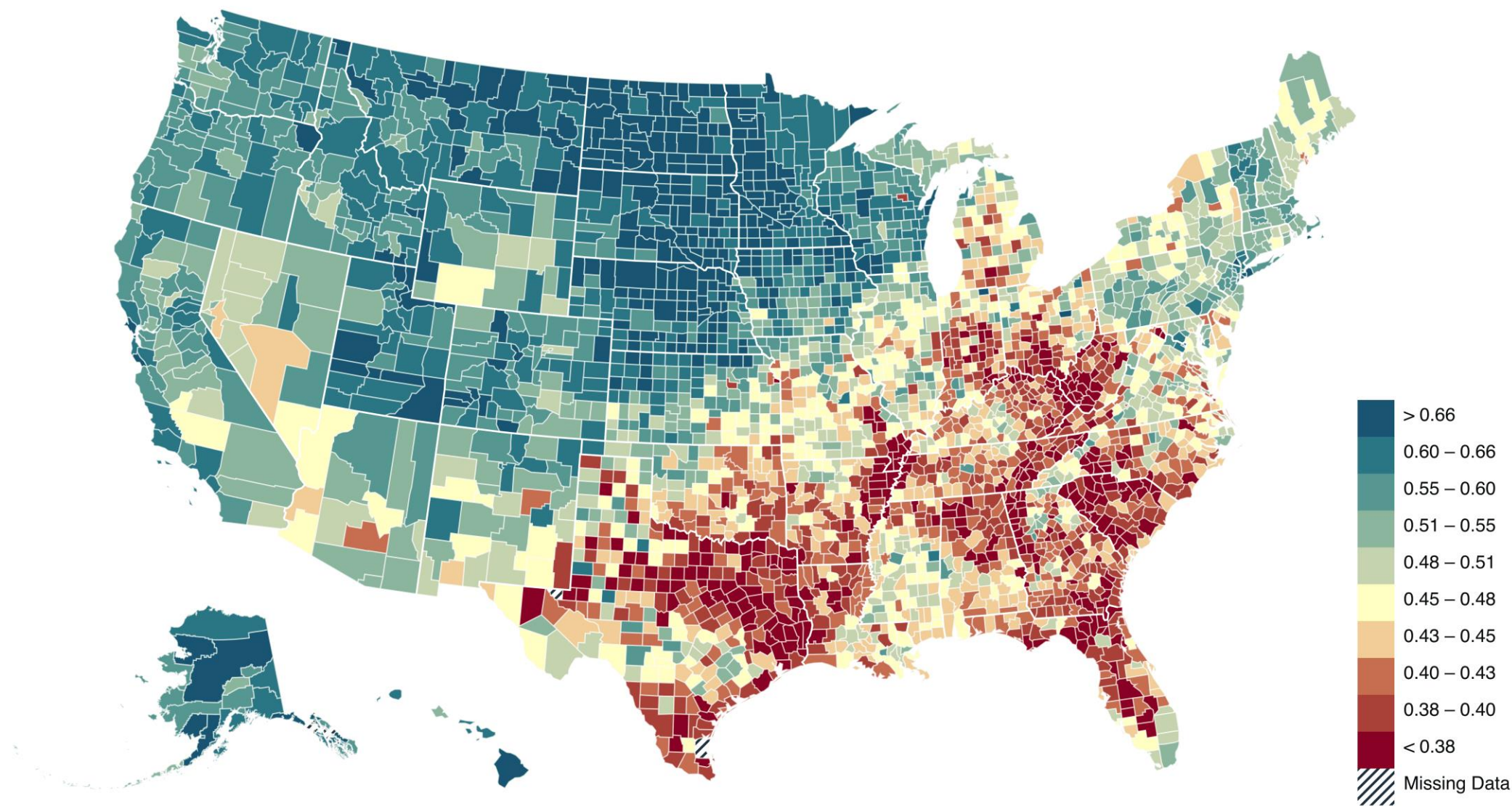
Follows 2 steps:

1. **Childhood exposure design:** Measure effect of childhood exposure to hometowns that have higher delinquency rates
2. **Mediation Analysis [stay tuned]:** Assess whether effect of place on income is a mediator



Repayment (No 90+ Day Delinquency)

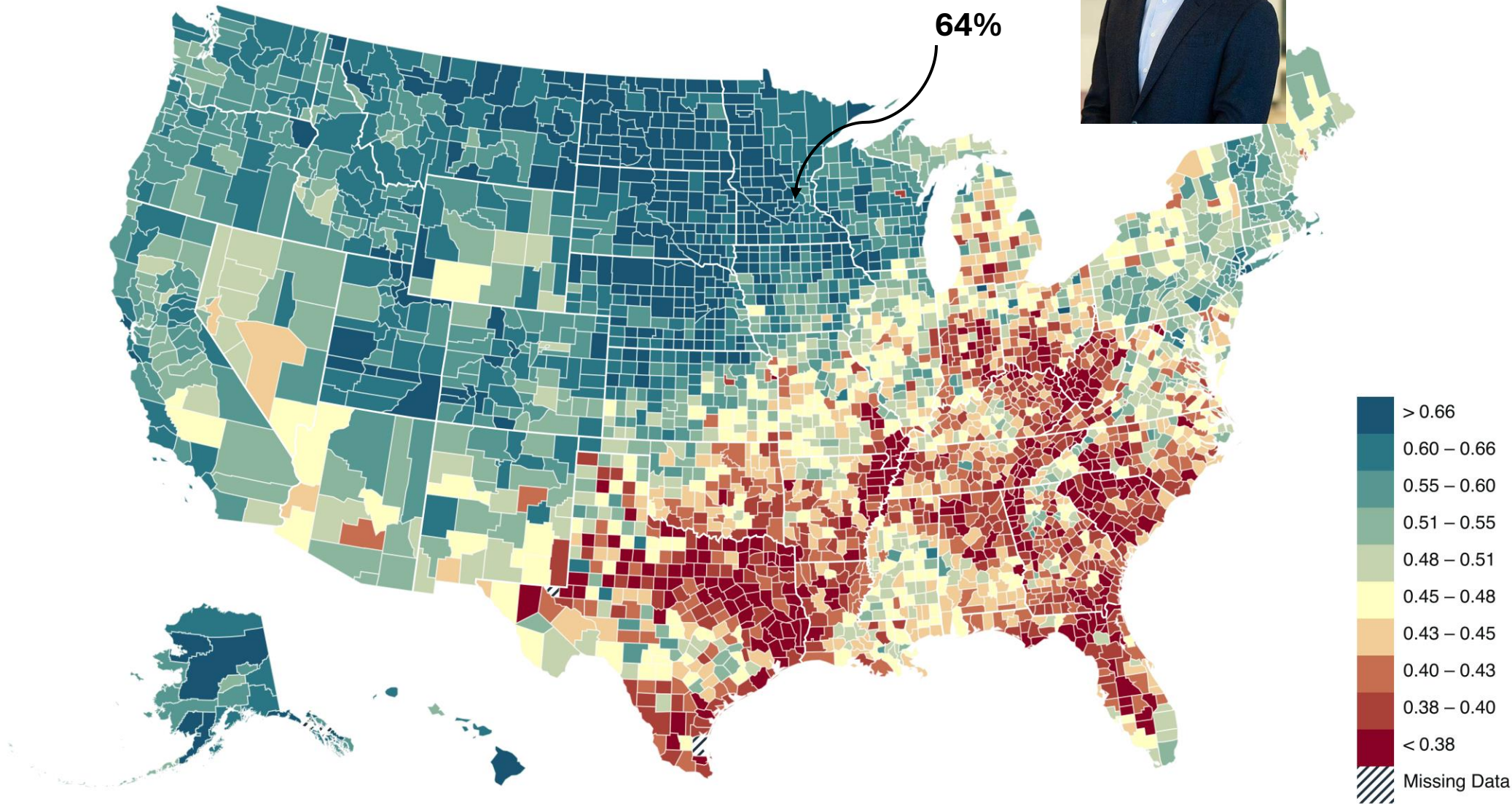
White 25th Percentile Parental Income (2020)



Repayment (No 90+ Day Delinquency)

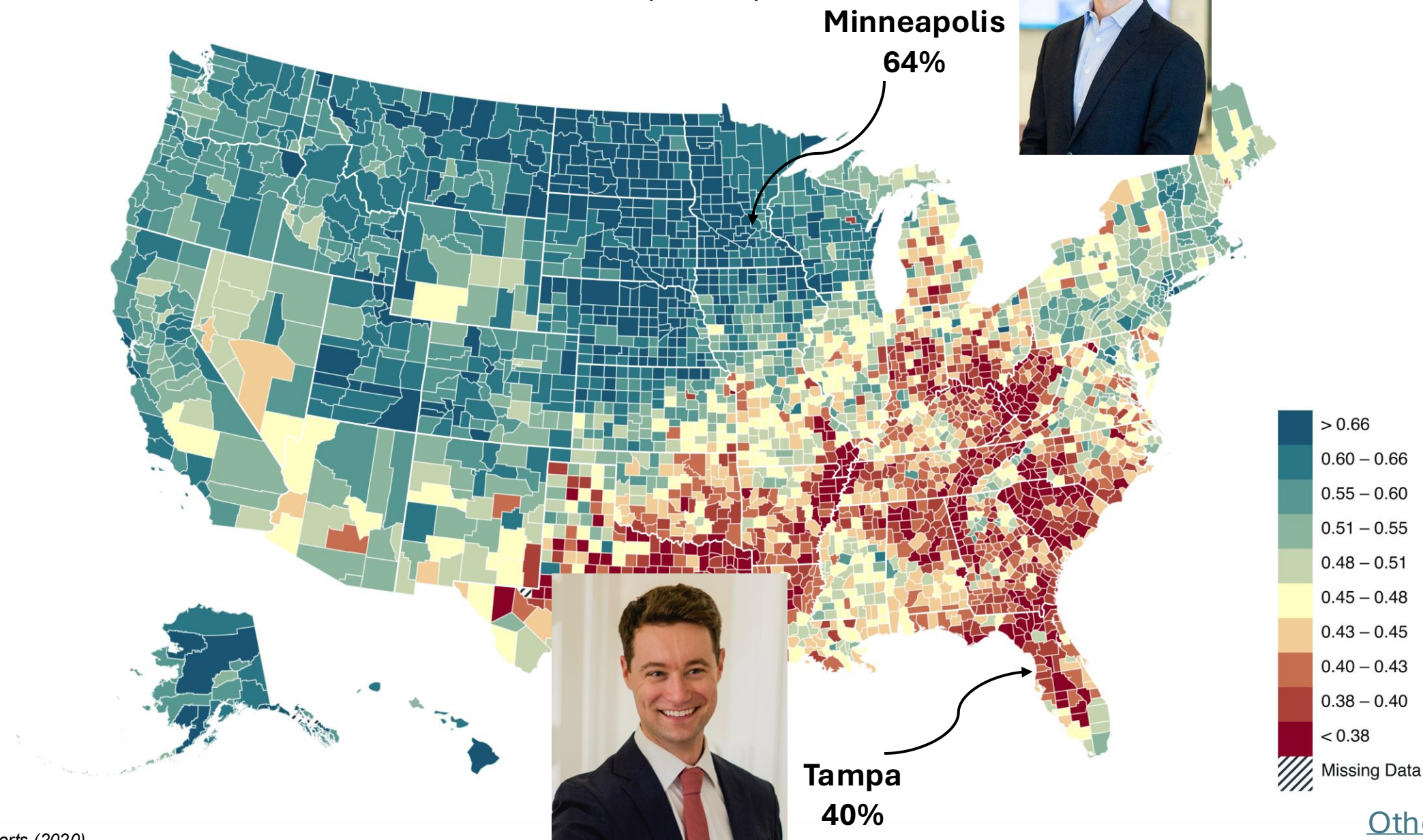
White 25th Percentile Parental Income (2020)

Minneapolis
64%

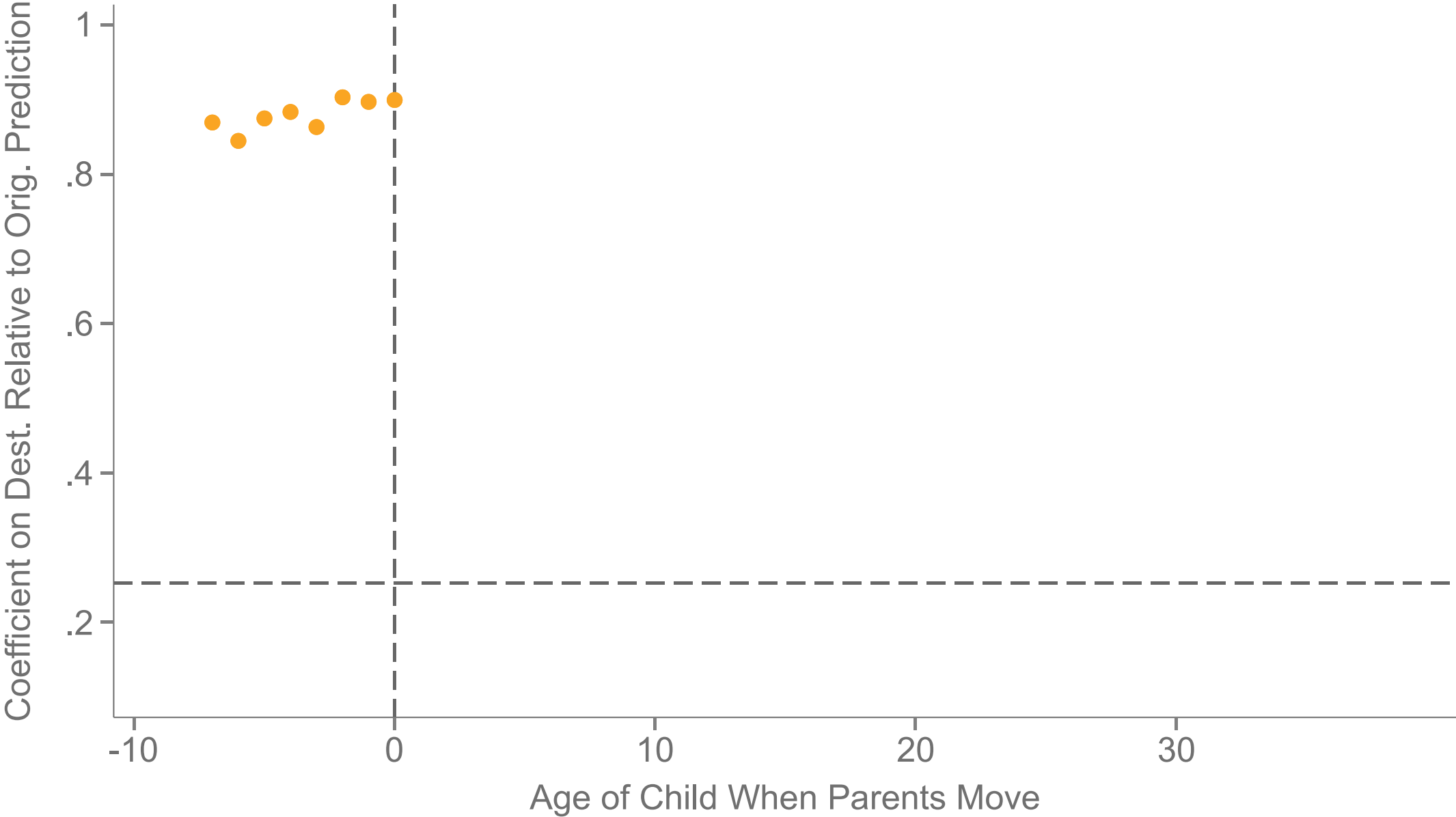


Repayment (No 90+ Day Delinquency)

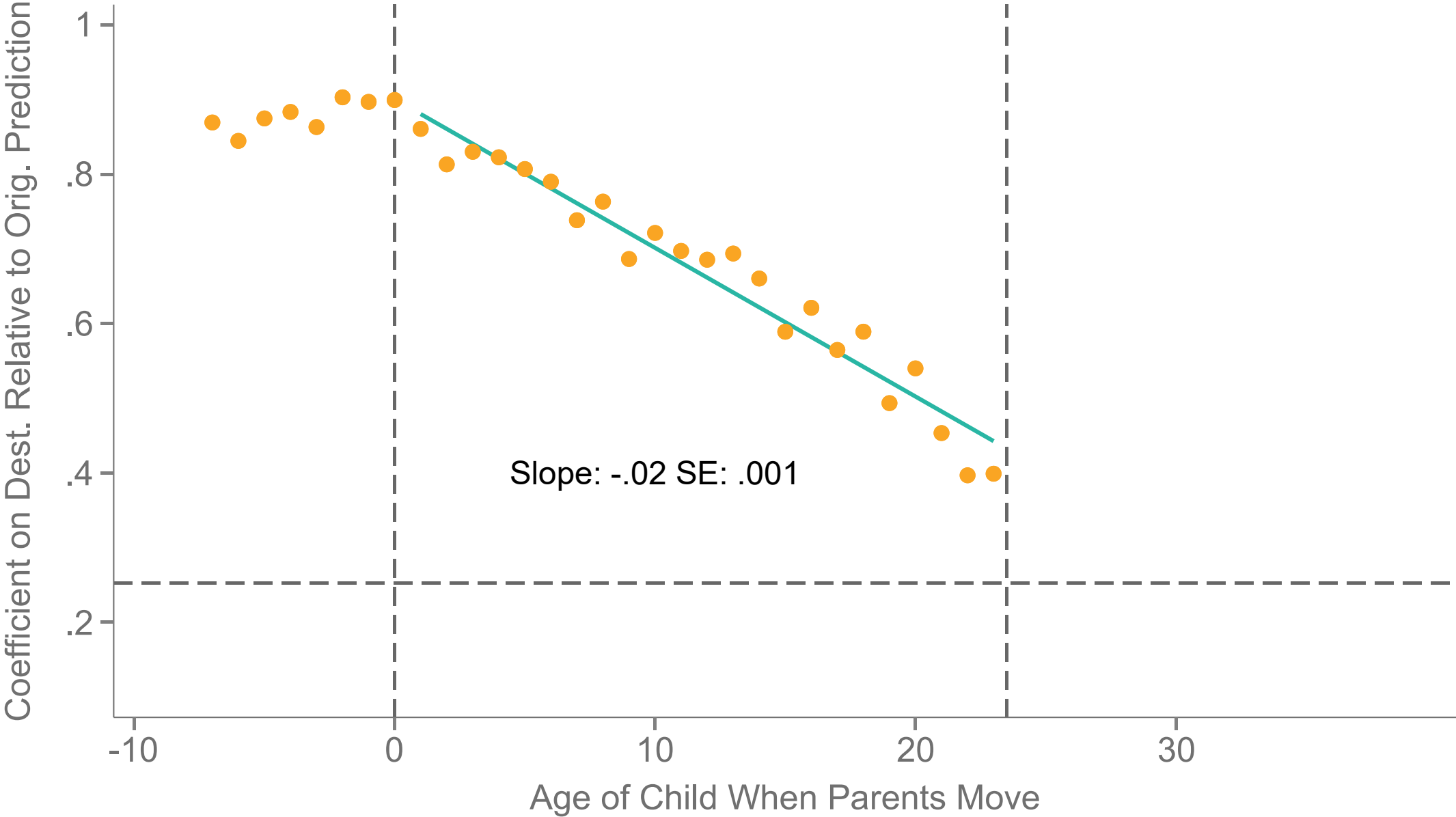
White 25th Percentile Parental Income (2020)



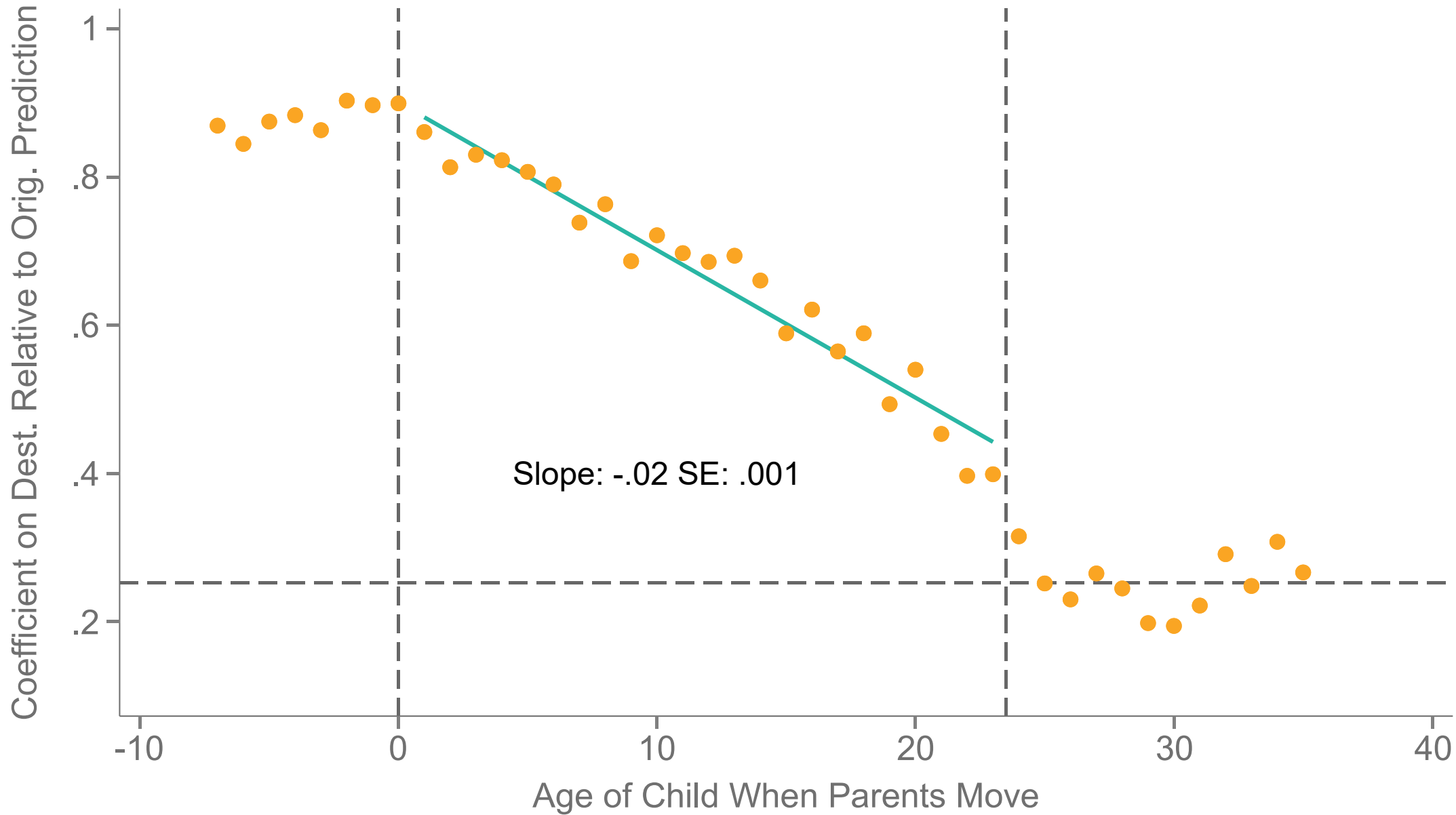
Childhood Exposure Effects for Repayment in 2004 (age 19-22)



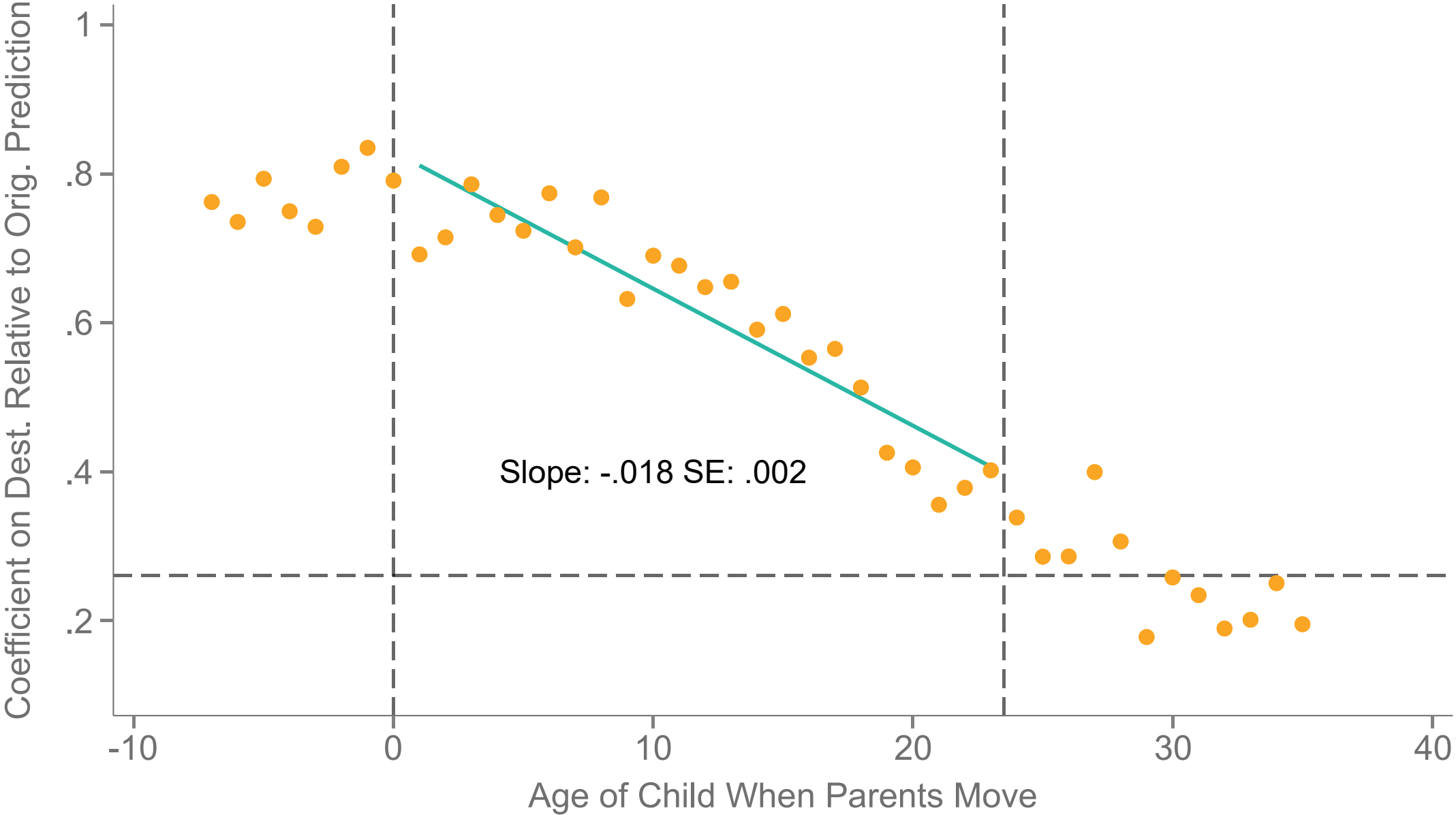
Childhood Exposure Effects for Repayment in 2004 (age 19-22)



Childhood Exposure Effects for Repayment in 2004 (age 19-22)



Childhood Exposure Effects for Repayment in 2004 (age 19-22) with Family FE



Summary

- Childhood inputs that are captured through exposure to place explains most of the gap in repayment across place (at least 60%)
- What about other gaps by race and parental income?
 - Race gap varies by hometown: 2x in San Francisco vs. Indianapolis
 - Most of this subset of the gap is due to the causal effect of childhood exposure
 - Suggests childhood inputs also influence race gap



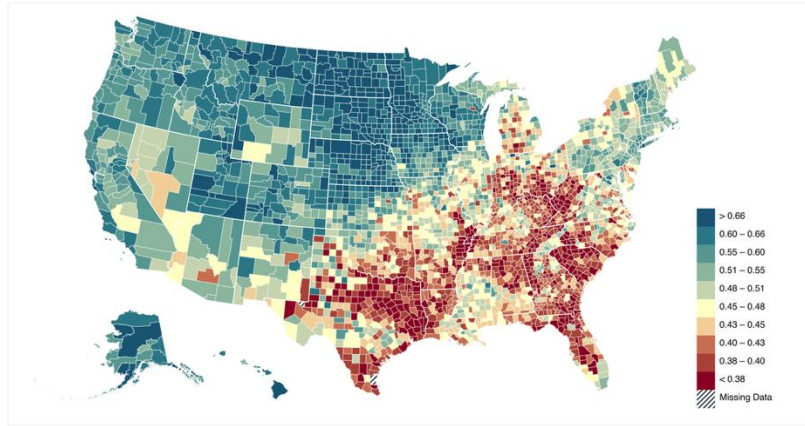
Childhood Exposure and the Race Gap

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

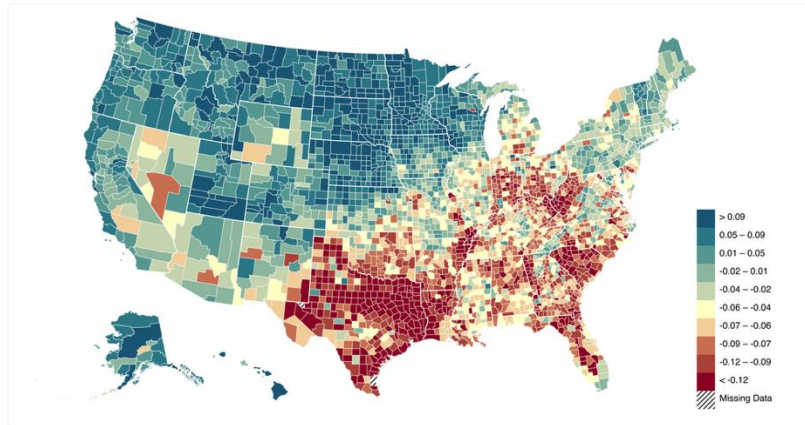


What Are These Inputs Generated Through Childhood Exposure?

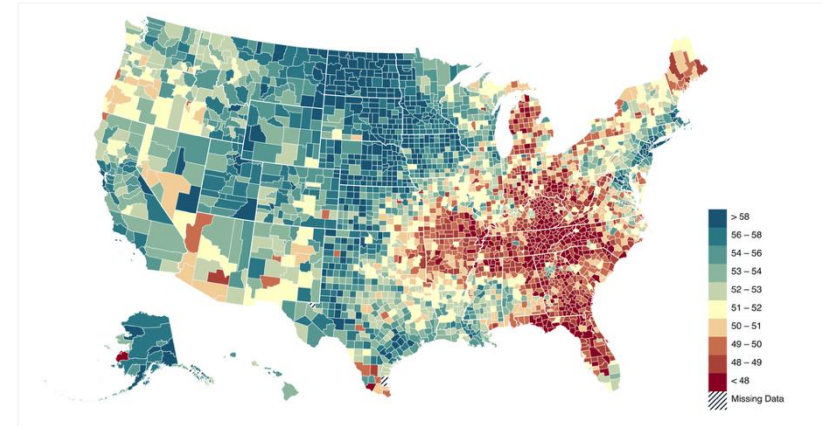
Spatial Correlation with Social Capital



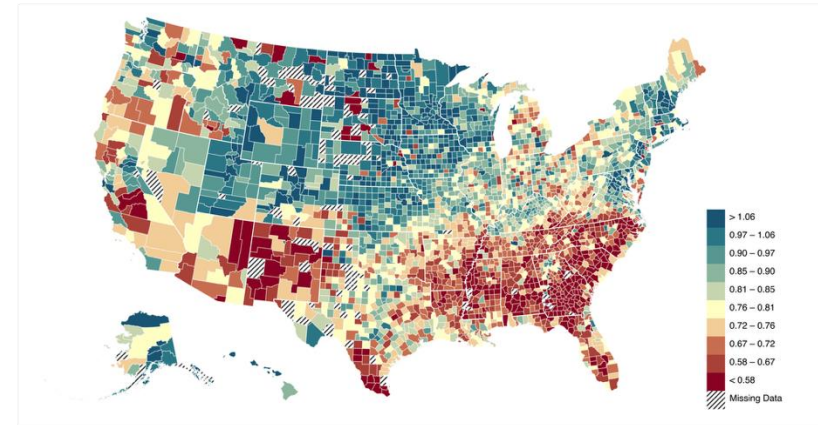
Repayment (Credit Bureau Data)



**Repayment
Conditional on Adult Income**



Upward Income Mobility (Tax Data)



**Cross-Class Friendships
(Facebook Data)**



Conclusion

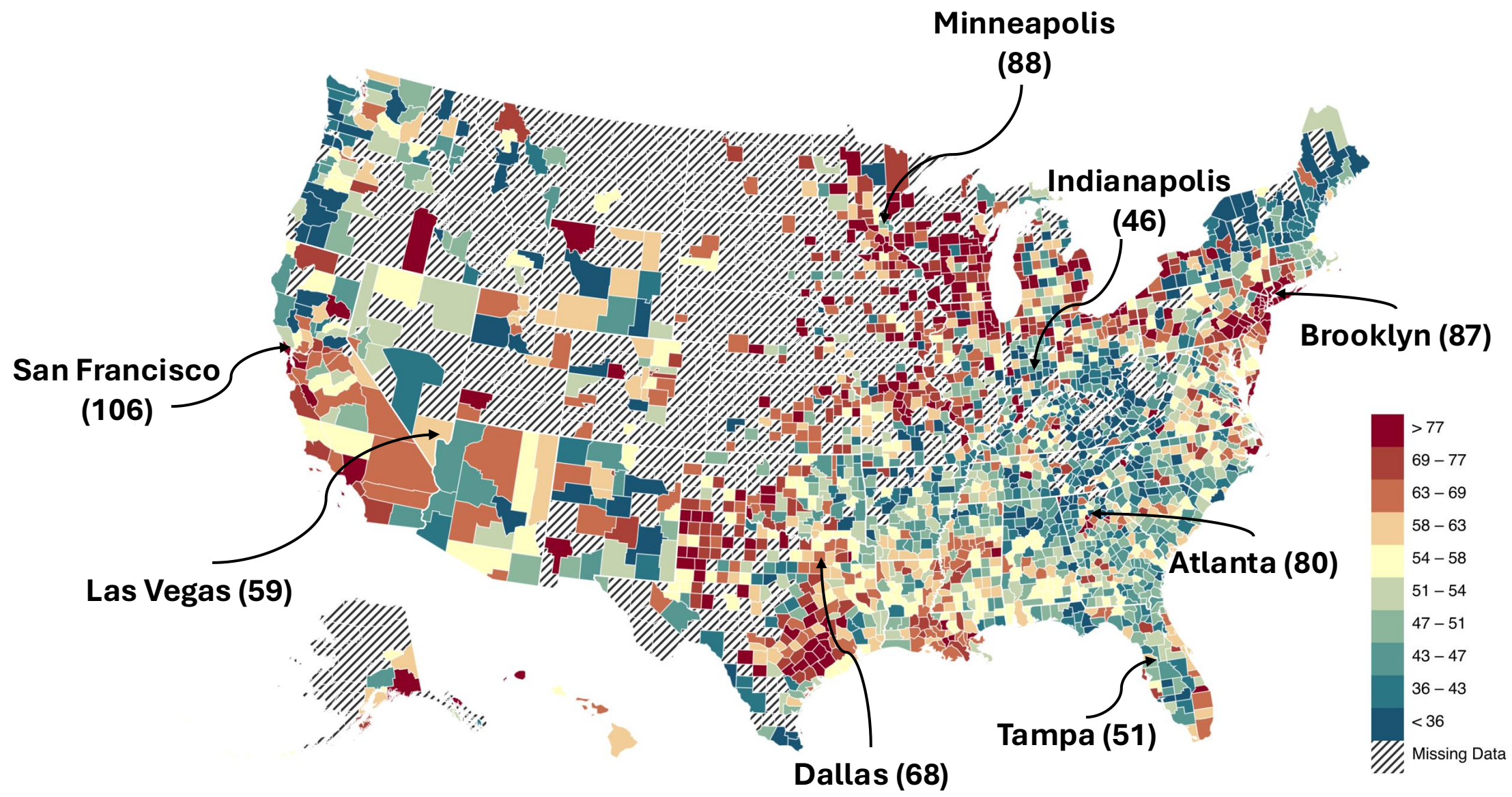
- Large differences in credit scores and non-repayment by race, class, and hometown, emerging by late 20s and persisting over the life cycle
- Income explains at most ~30% of the gaps by race, place, and hometown; childhood exposure to place explains more than 60% of the hometown gap
- Strength of cross-class friendships are correlated with both repayment and upward income mobility
- Credit constraints in adulthood have their roots in childhood



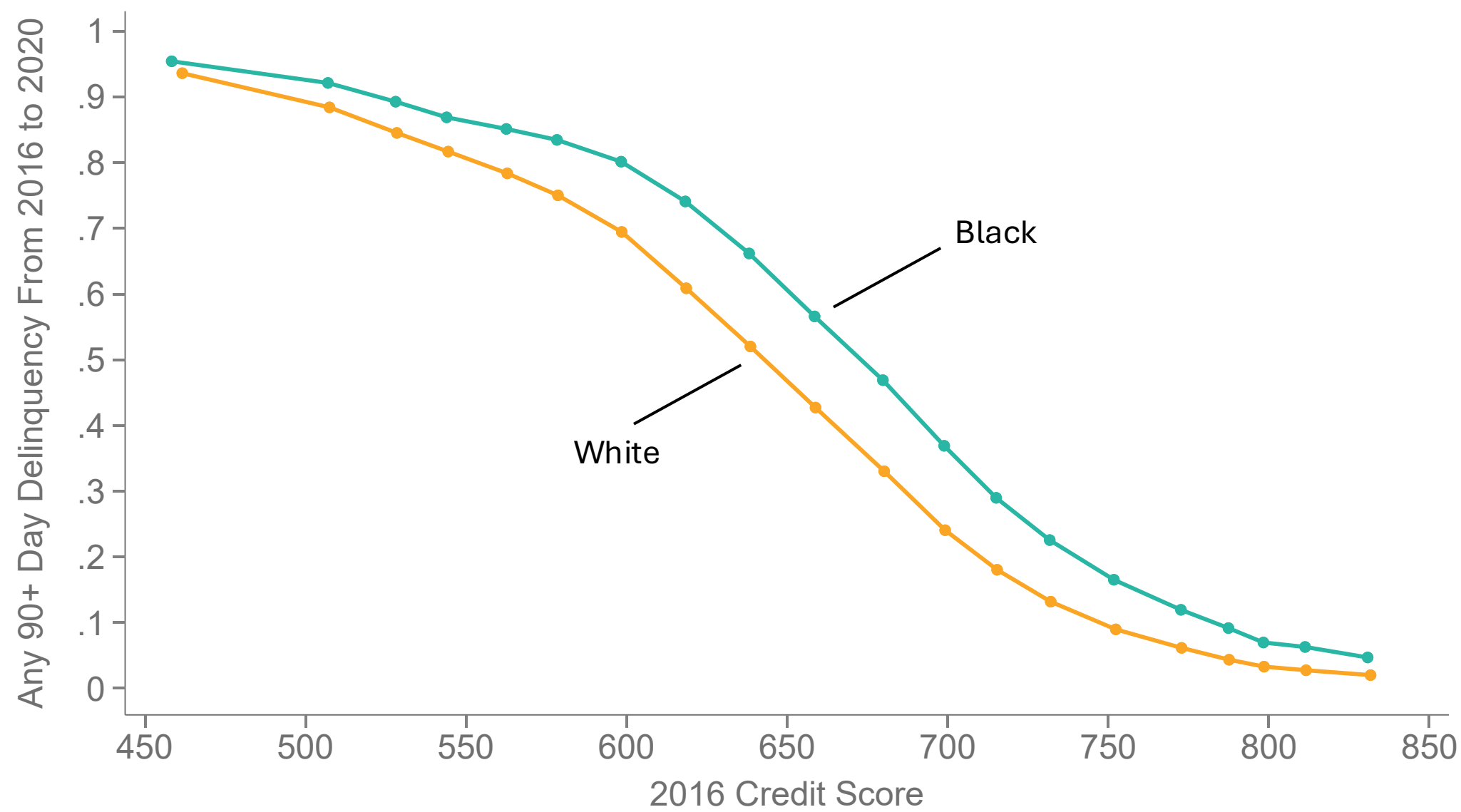
Appendix



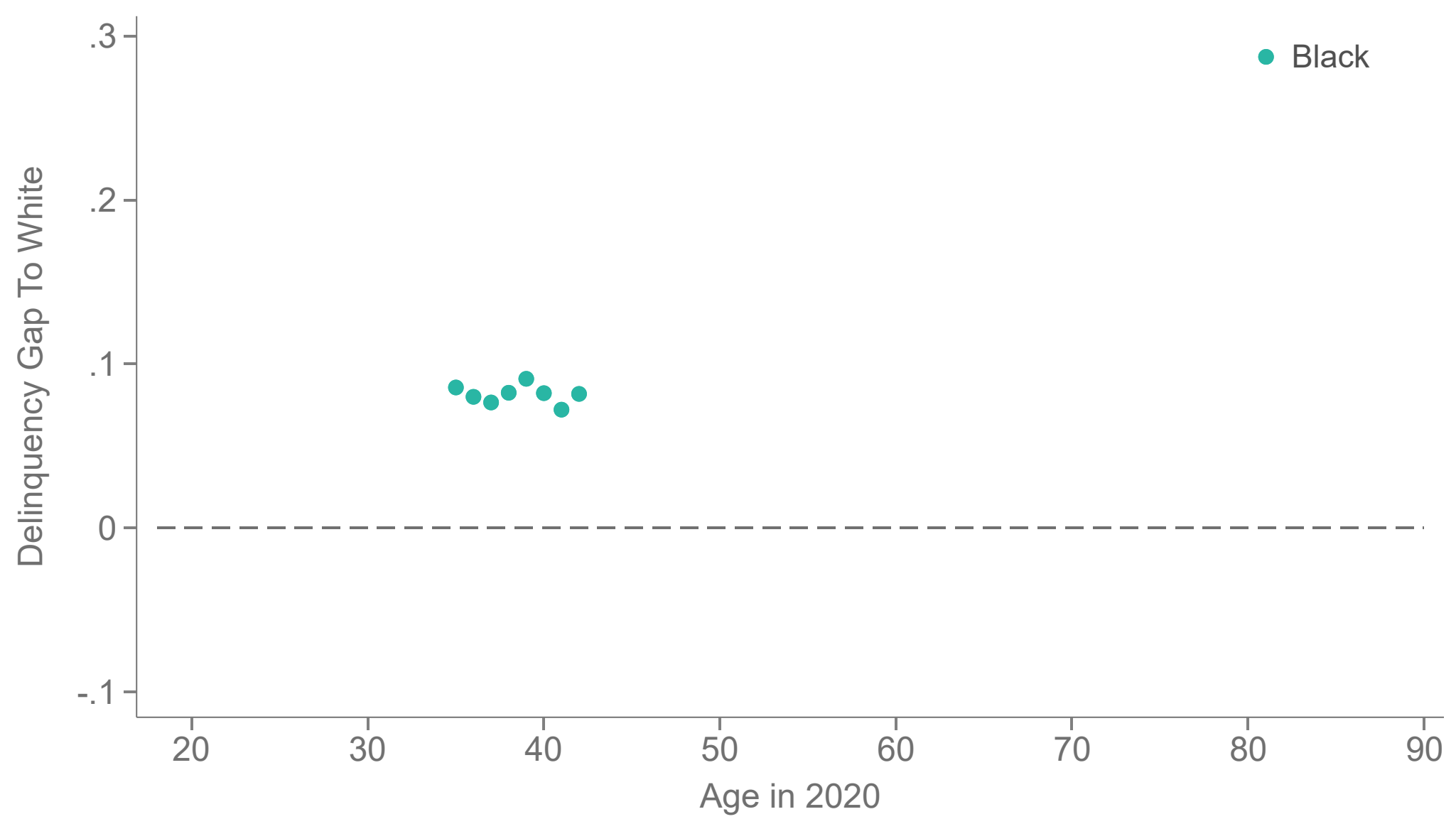
Credit Score Black-White Gap by County



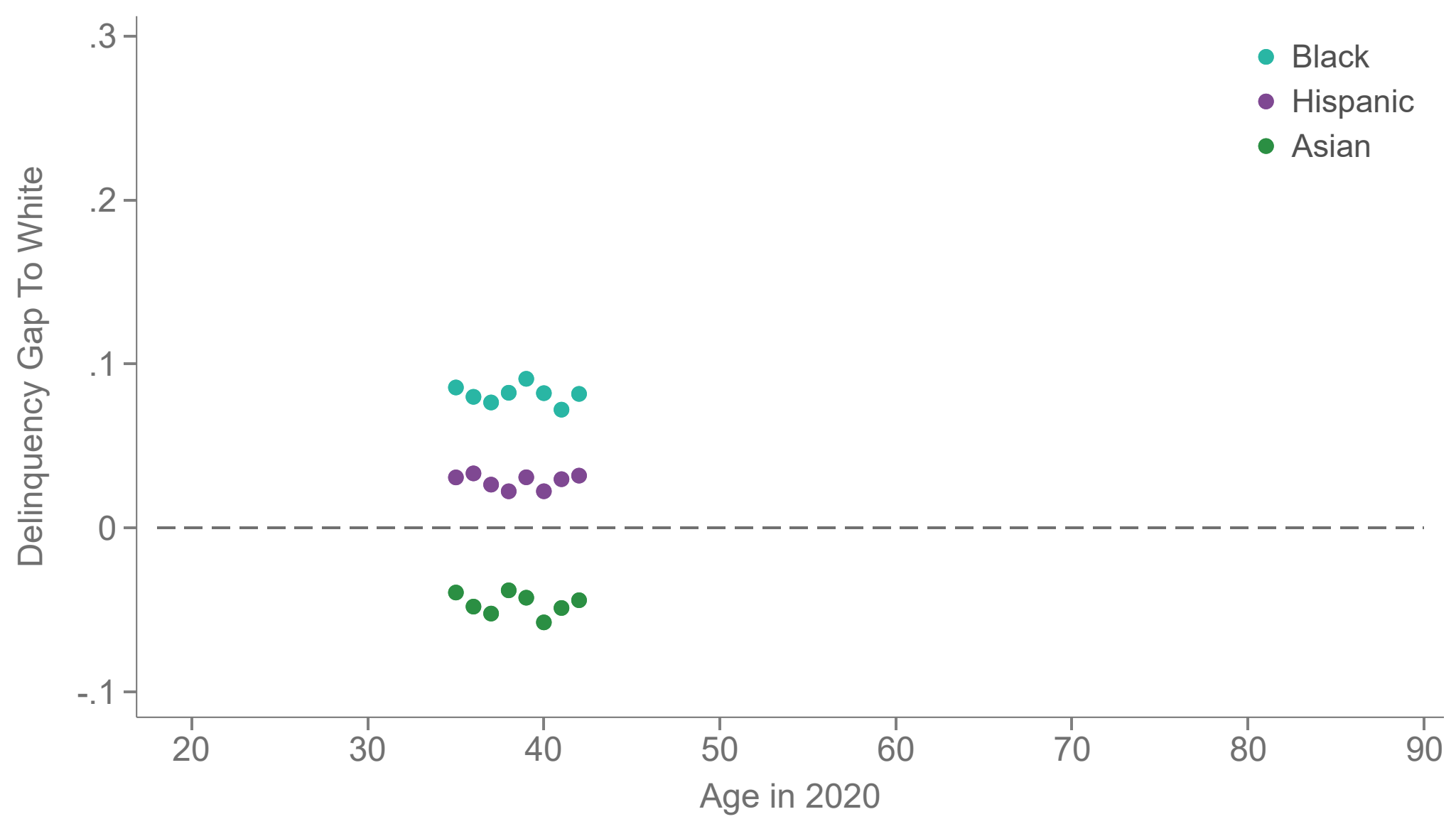
Racial Calibration: Credit Scores are Predictive of Future Delinquency



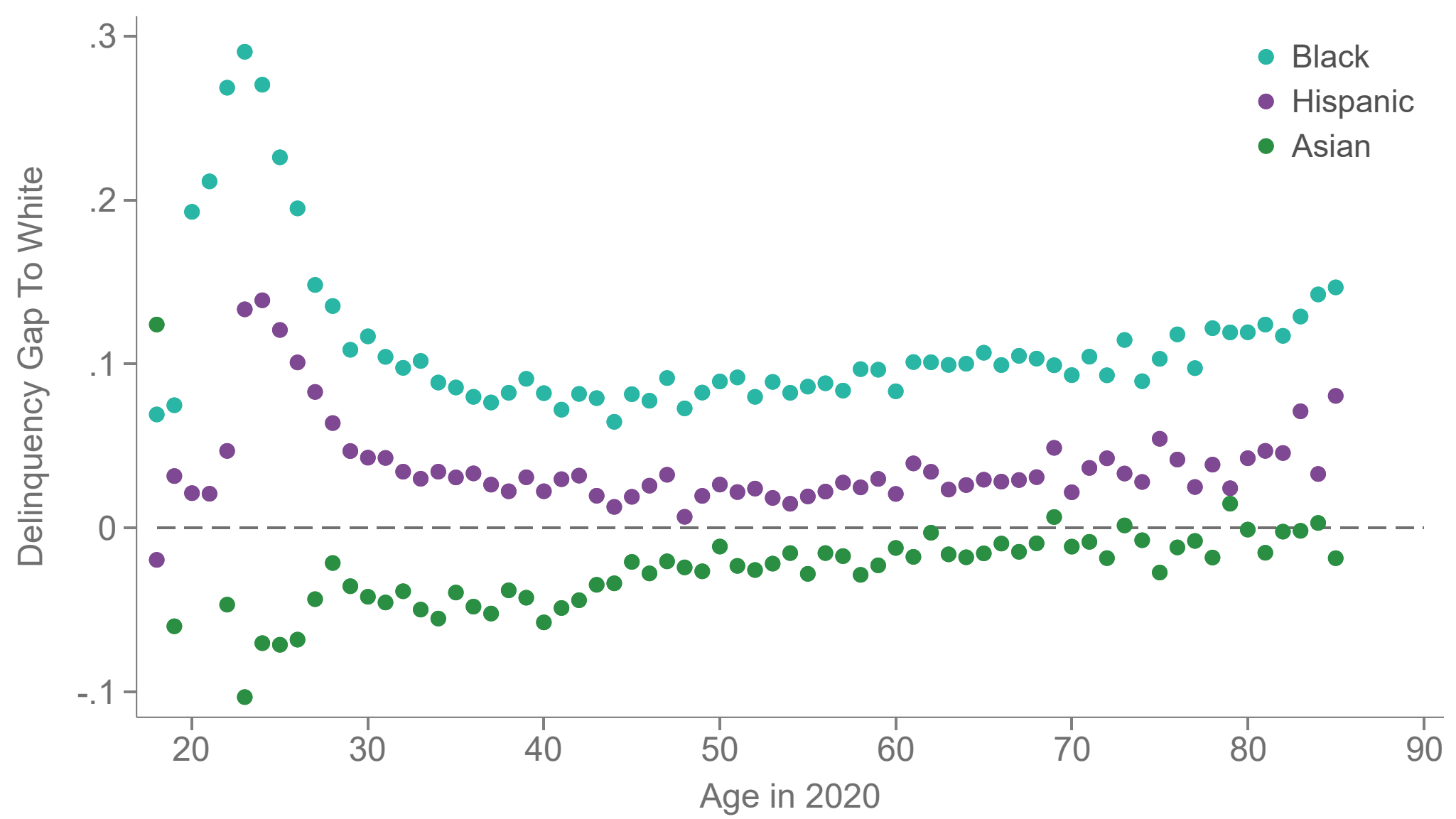
Racial Calibration of Credit Score by Age



Racial Calibration of Credit Score by Age



Racial Calibration of Credit Score by Age



Summary

- **Calibration:** Credit score gaps understate differences in underlying propensities to repay across groups

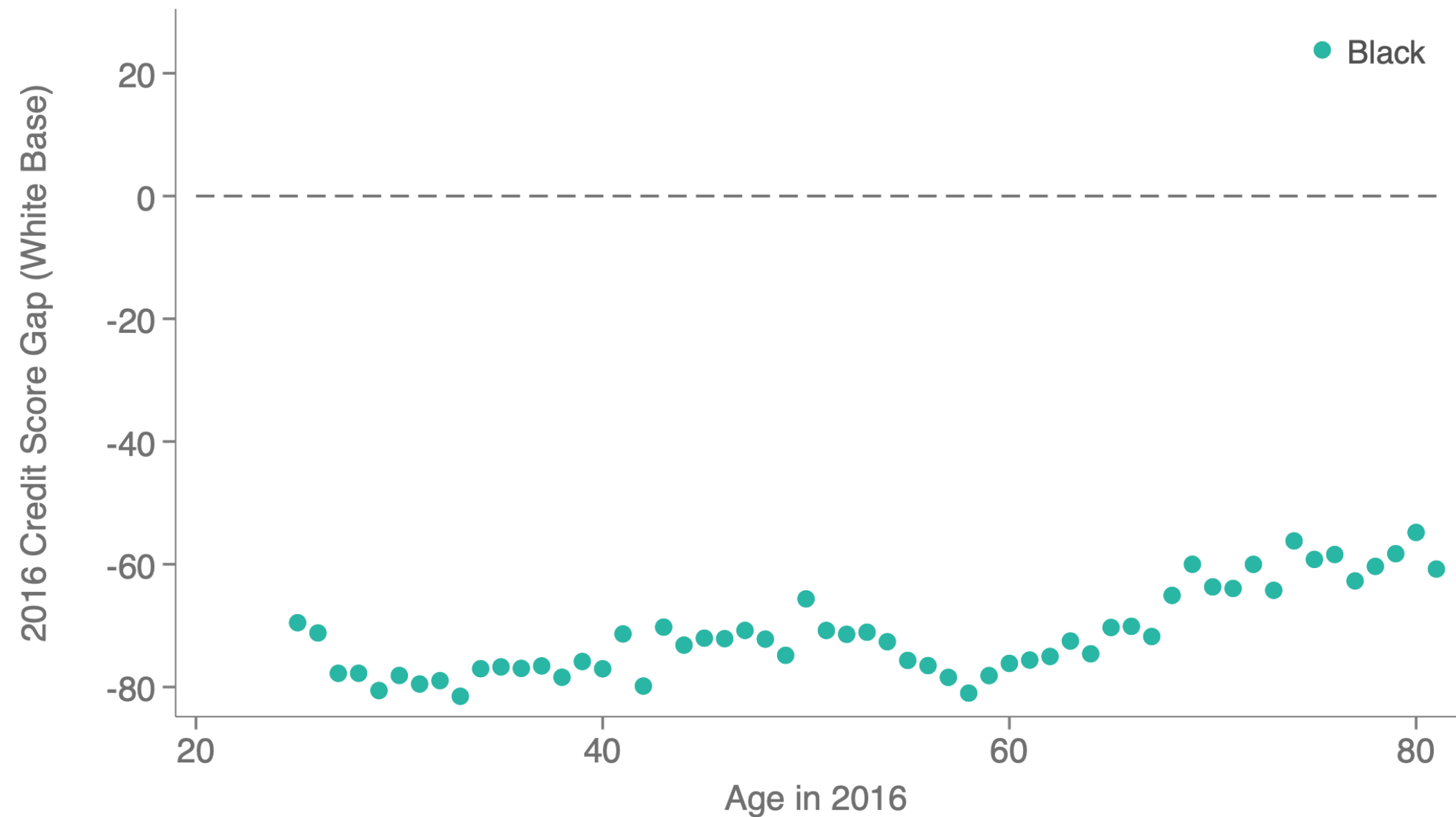
Summary

- **Calibration:** Credit score gaps understate differences in underlying propensities to repay across groups
- A different notion of “Bias” is **Balance** [Arnold, Dobbie and Hull (2022,2025)]
 - Conditional on the outcome, do different groups receive different scores

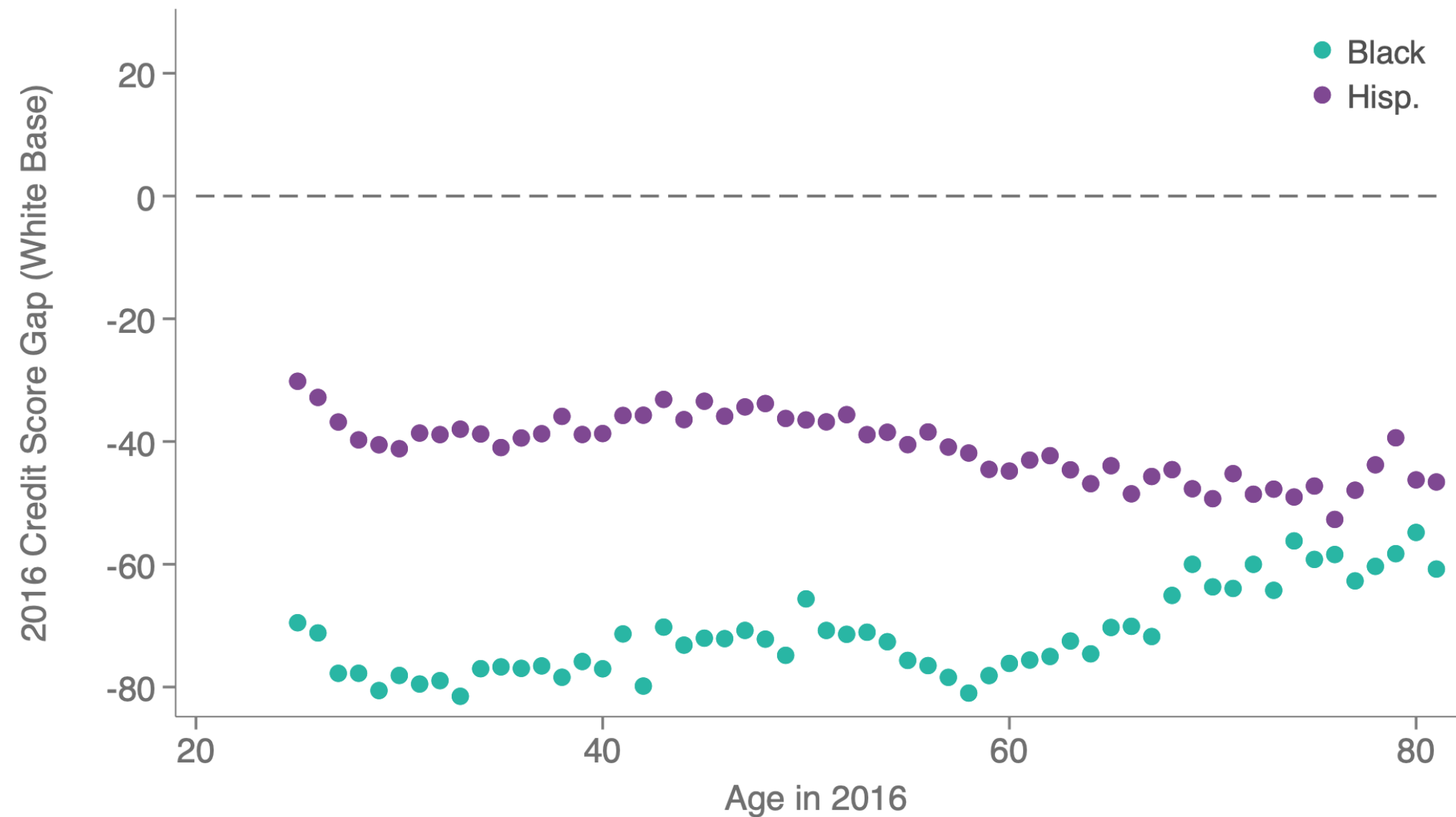
Summary

- **Calibration:** Credit score gaps understate differences in underlying propensities to repay across groups
- A different notion of “Bias” is **Balance** [Arnold, Dobbie and Hull (2022,2025)]
 - Conditional on the outcome, do different groups receive different scores
- Take the set of people who do NOT experience a 90+ day delinquency between 2016-2020 study the difference in credit scores
- Start with differences in credit scores by race (relative to White), separately by age

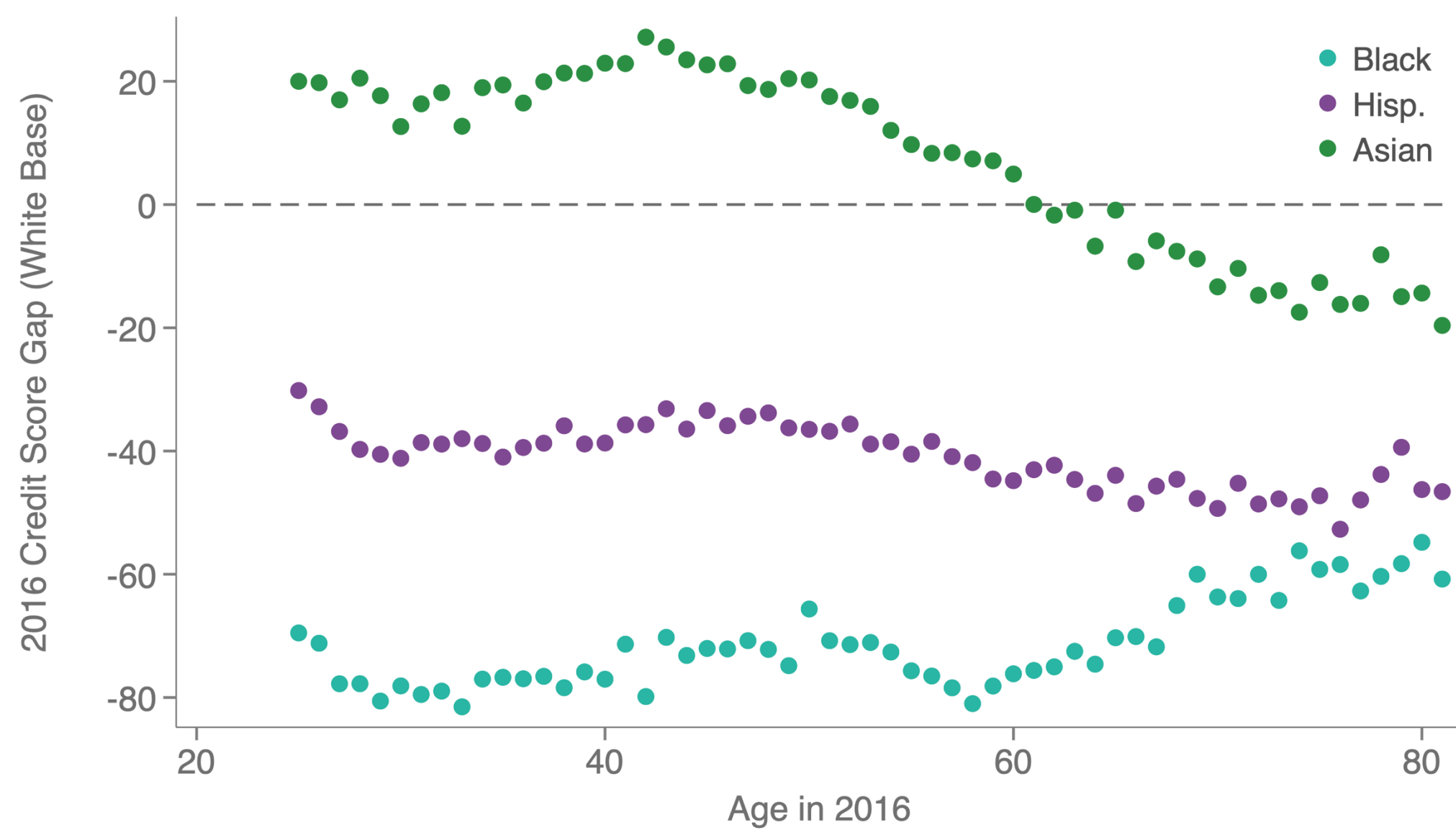
Racial Balance by Age: Average Score Among Those Without 90+ Delinquency



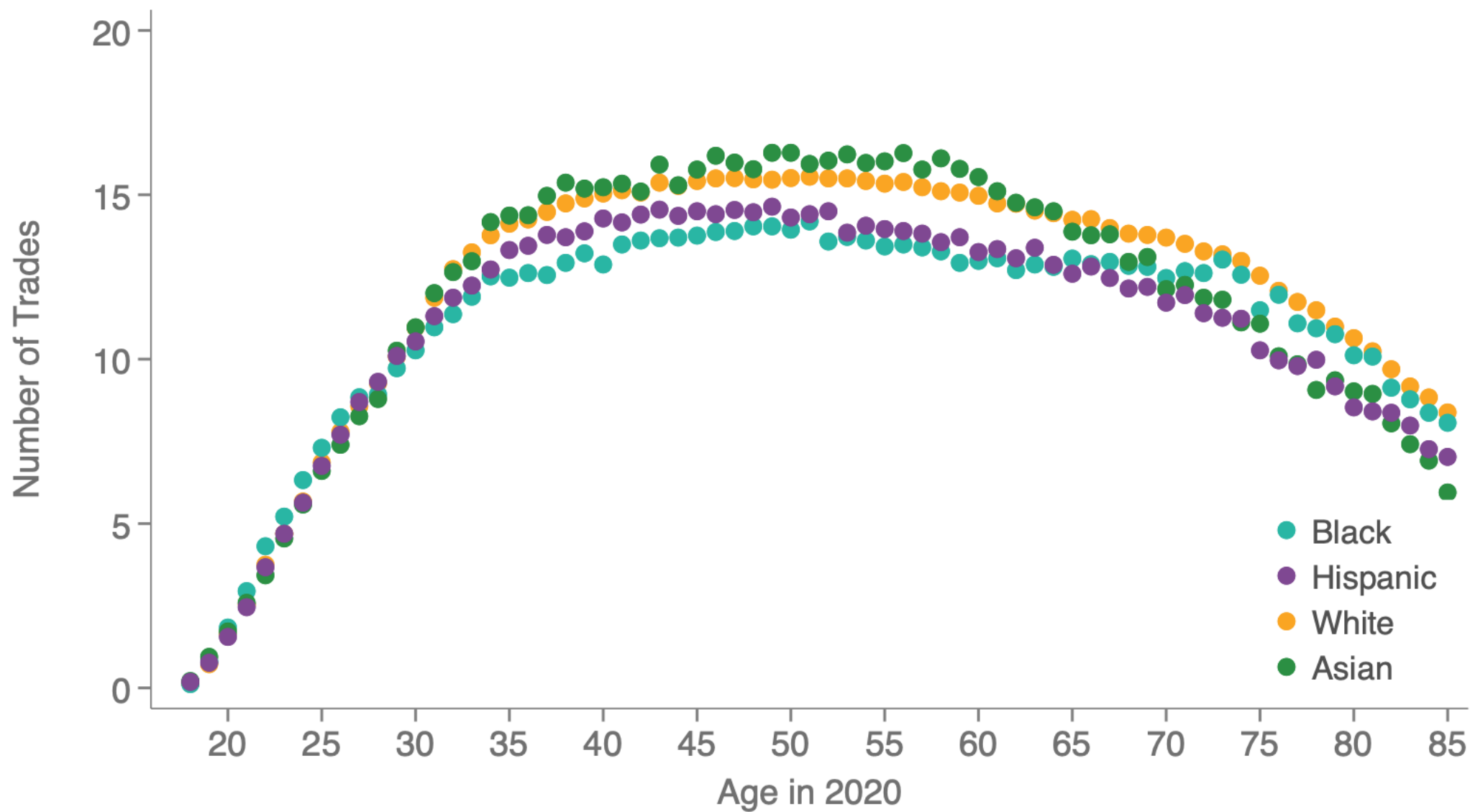
Racial Balance by Age: Average Score Among Those Without 90+ Delinquency



Racial Balance by Age: Average Score Among Those Without 90+ Delinquency



Number of Tradelines by Age, by Race



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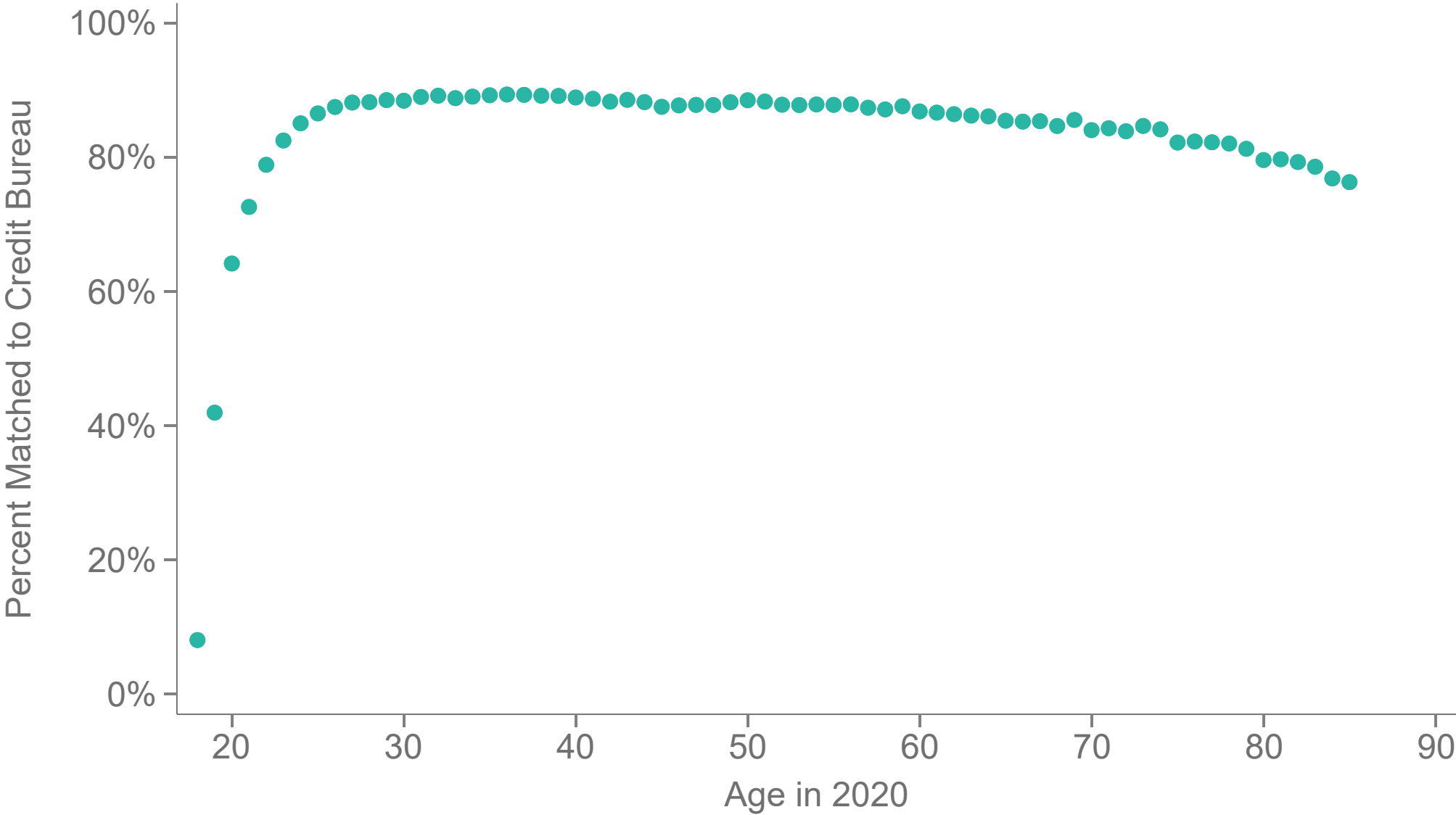
- [Credit Invisibles](#)
- [Credit Score Robustness](#)
- [Household Balance Sheets](#)
- [Movers and Correlates of Place](#)
- [The Rise of Student Loans](#)
- [Authorized Users](#)
- [Maps](#)
- [Takeup of Credit](#)
- [Social Capital](#)
- [Lifecycle of Late Payments By Tradeline](#)
- [Calibration Bias Among Perfect Borrowers](#)



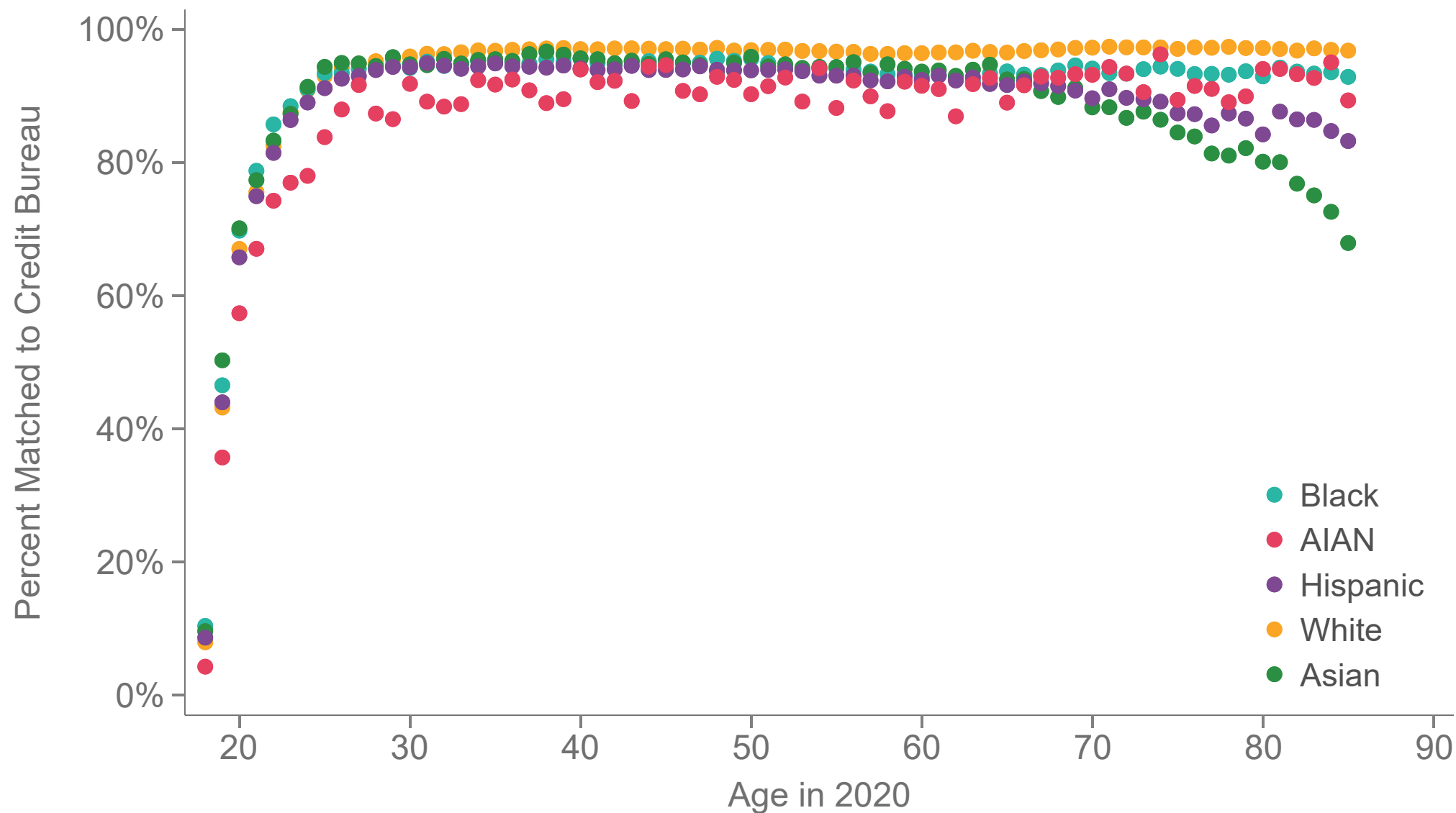
Credit Invisibles



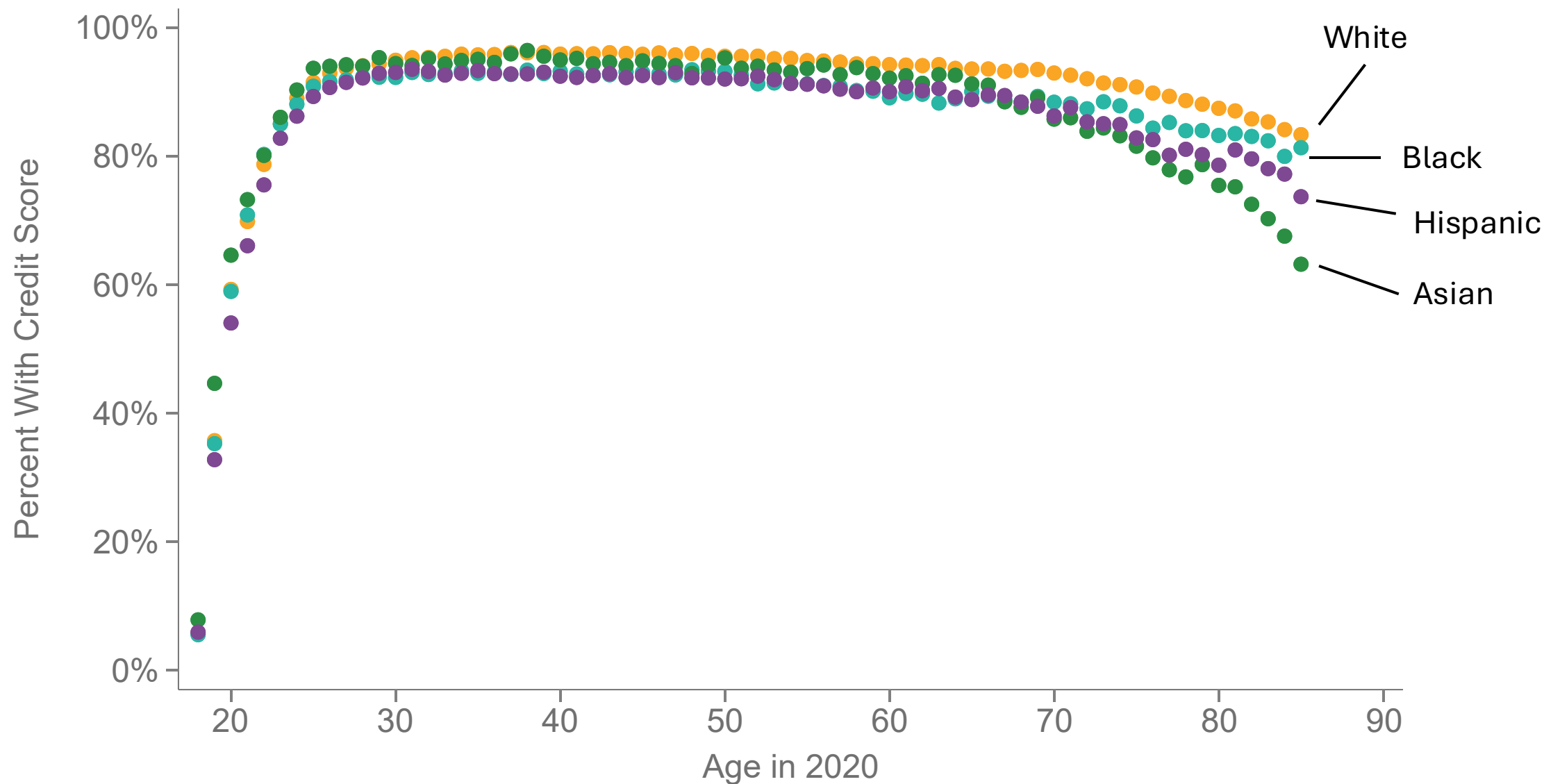
Fraction of People with SSN that have a Credit File



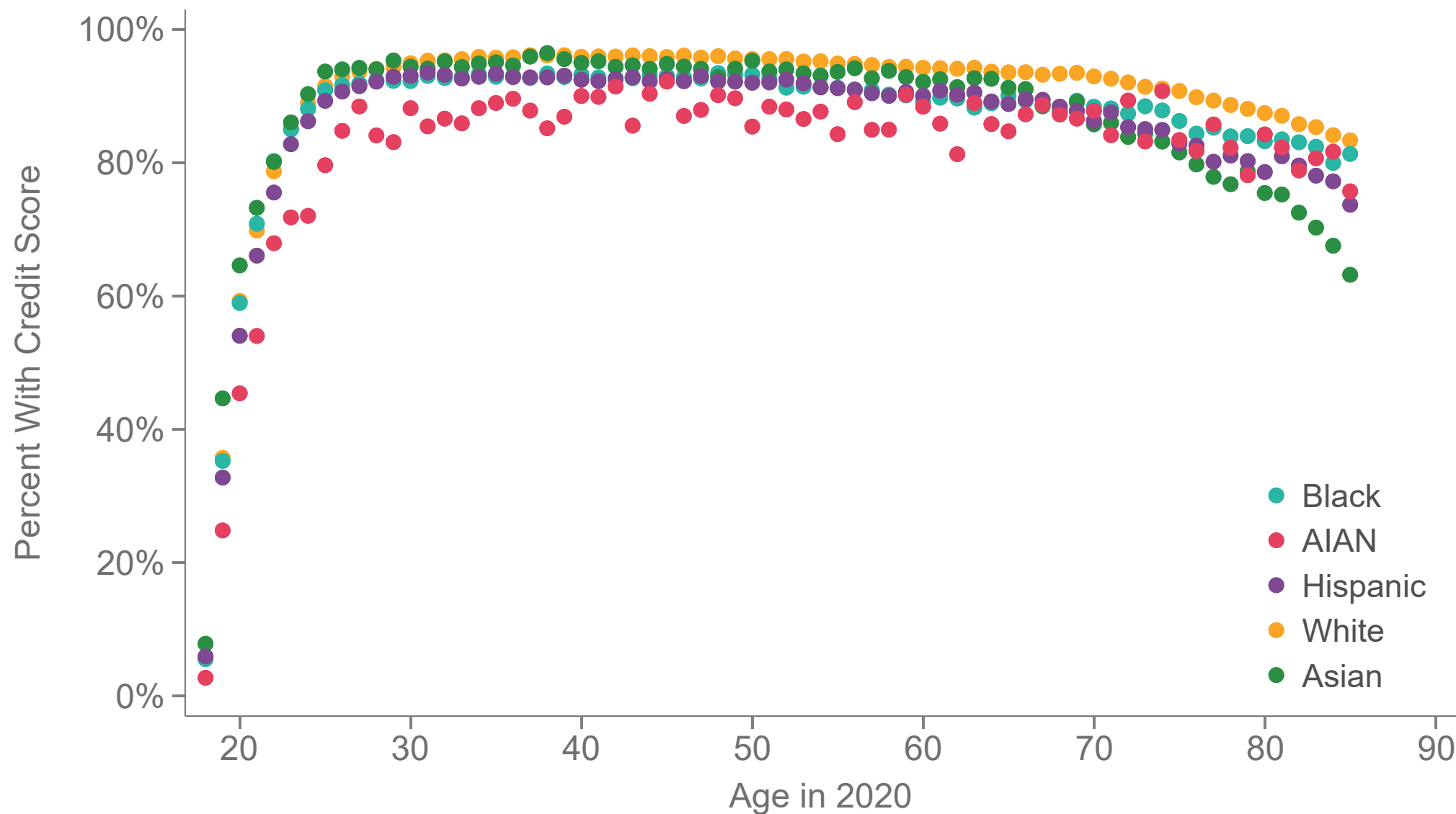
Fraction of People with a Credit File, by Race



Credit Score (VantageScore 4.0) Rates By Age and Race



Credit Score (VantageScore 4.0) Rates By Age and Race



Further Details on Credit Scores

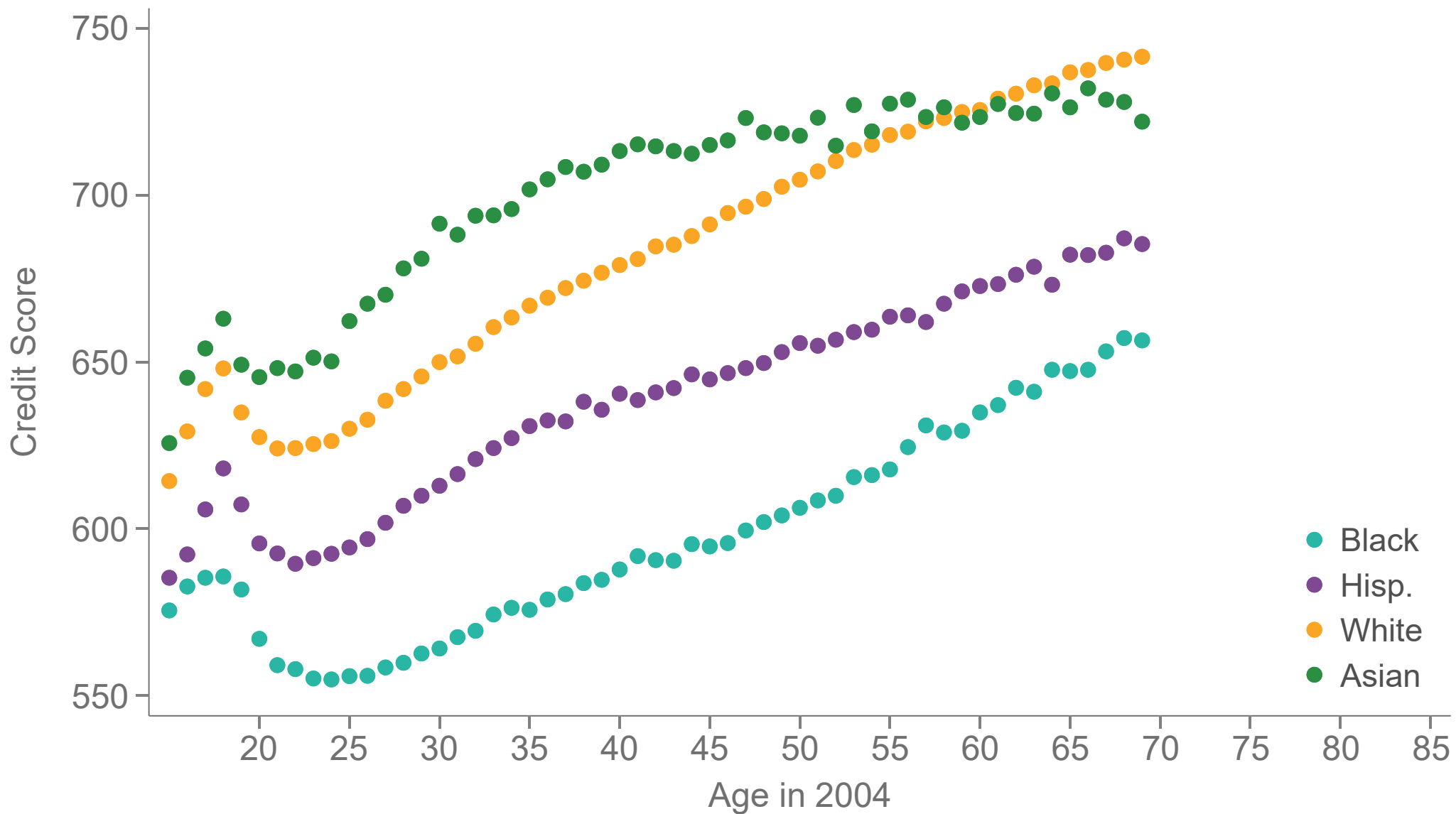
	Avg. Credit Score (Population)	Avg. Credit Score	Median Credit Score	Median Credit Score w/Zeros
White	719	701	719	712
Black	621	601	581	571
Asian	745	741	781	776
Hispanic	670	659	655	644
AIAN	641	622	602	583



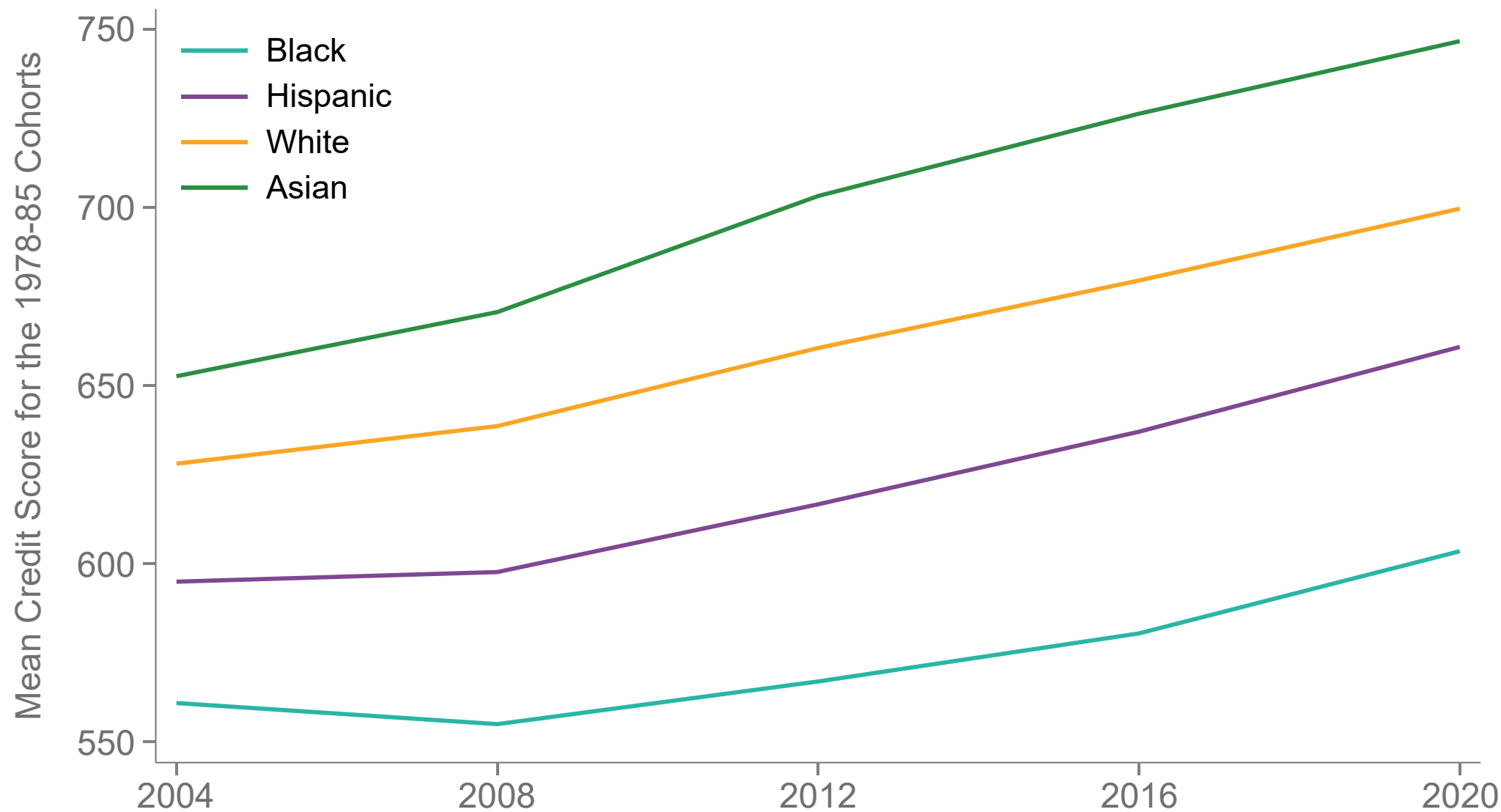
Credit Score Robustness



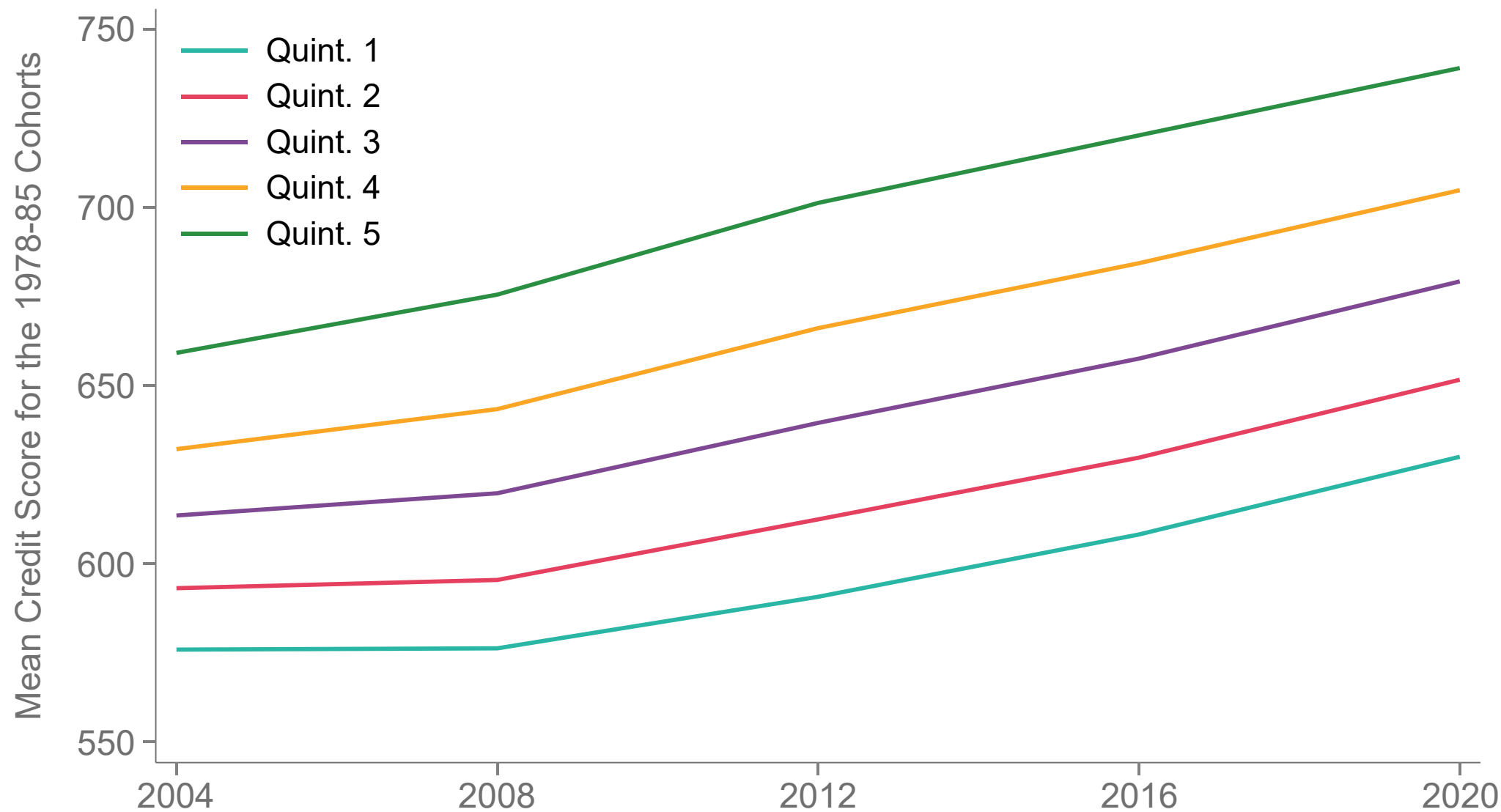
Credit Scores by Age and Race in 2004



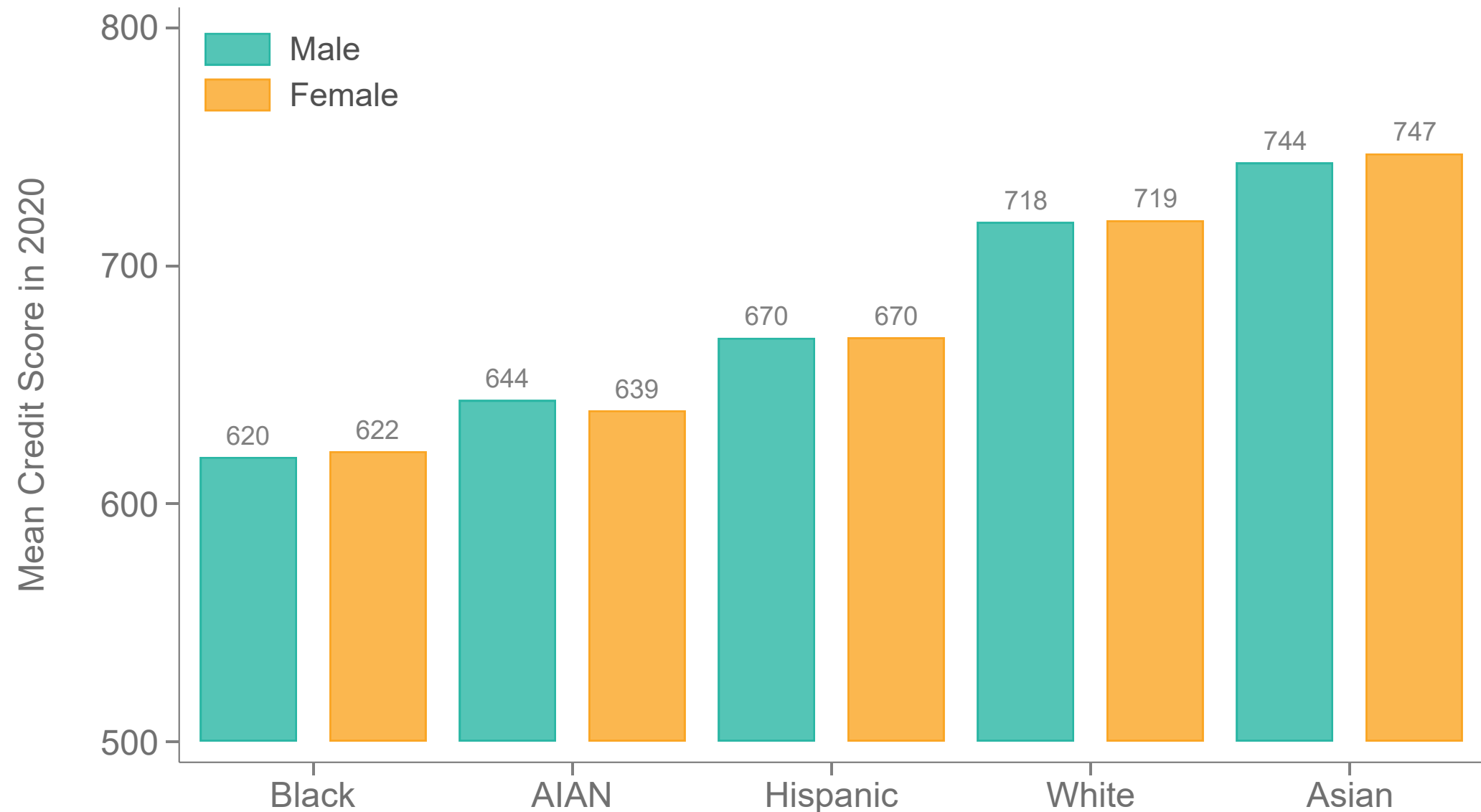
Credit Score Progression Over Time By Race



Credit Score Progression Over Time By Class



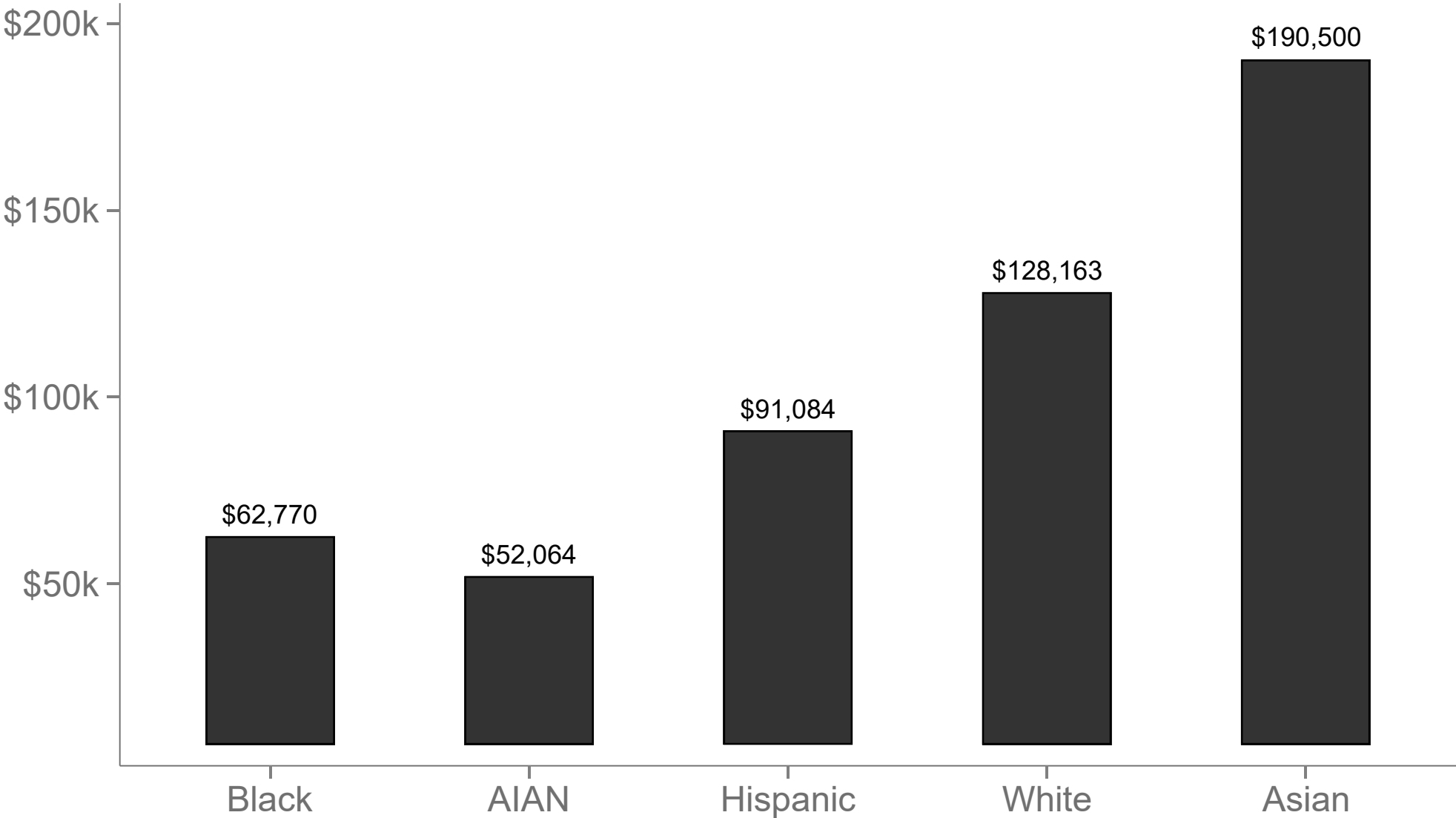
Credit Score by Race and Gender in 2020



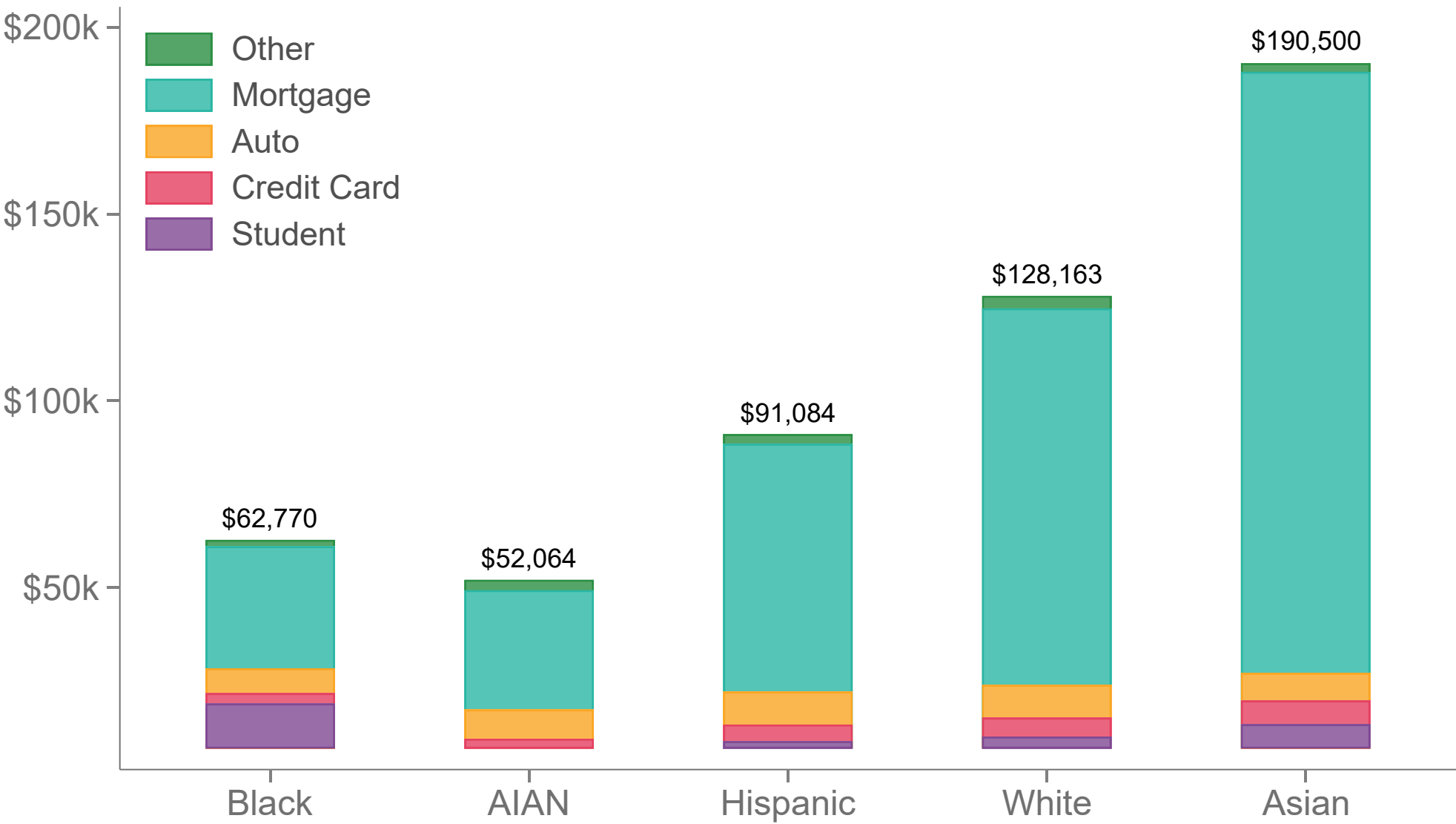
Household Balance Sheets



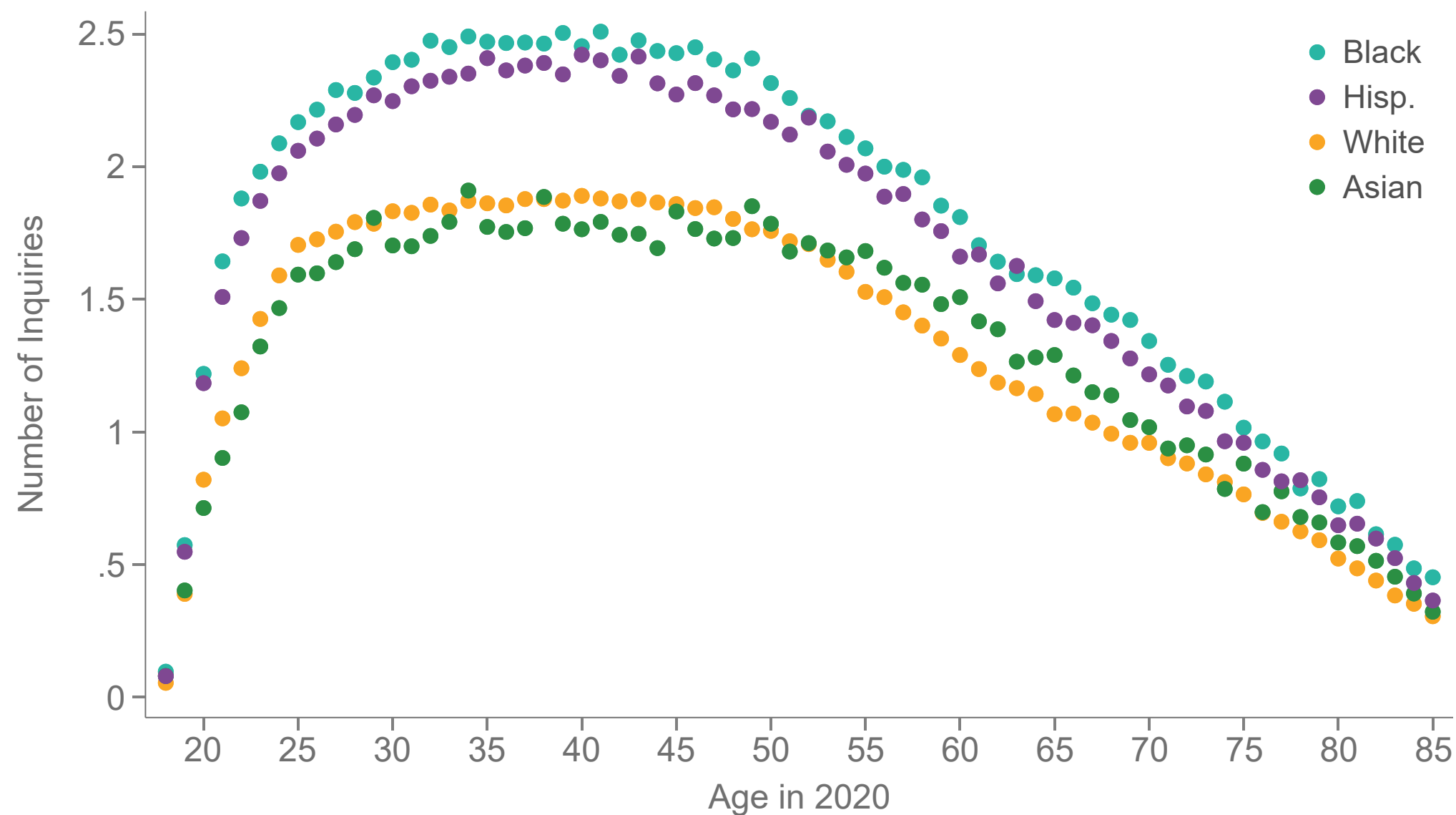
Average Debt Balance by Race 2020



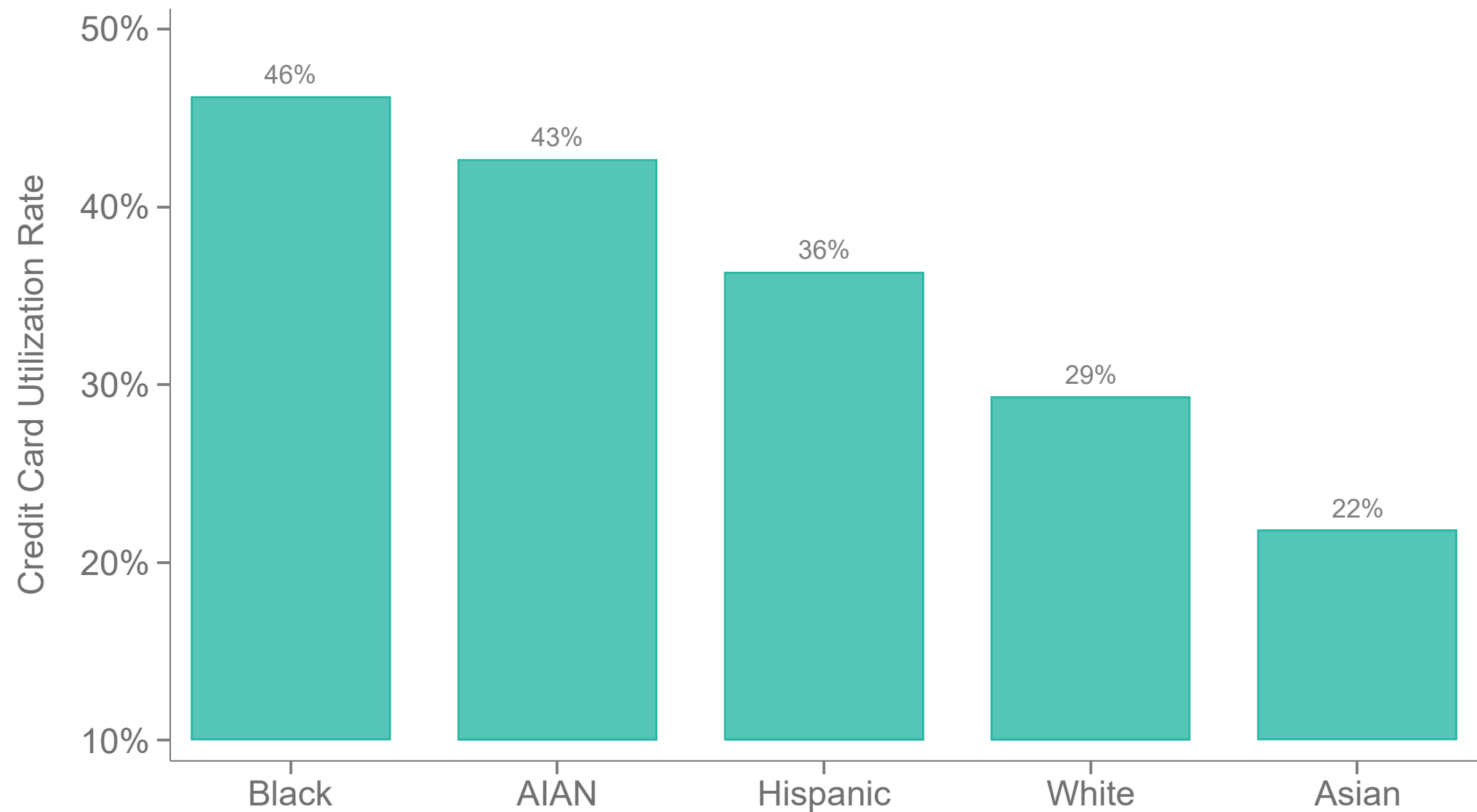
Composition of Average Debt Balance by Race 2020



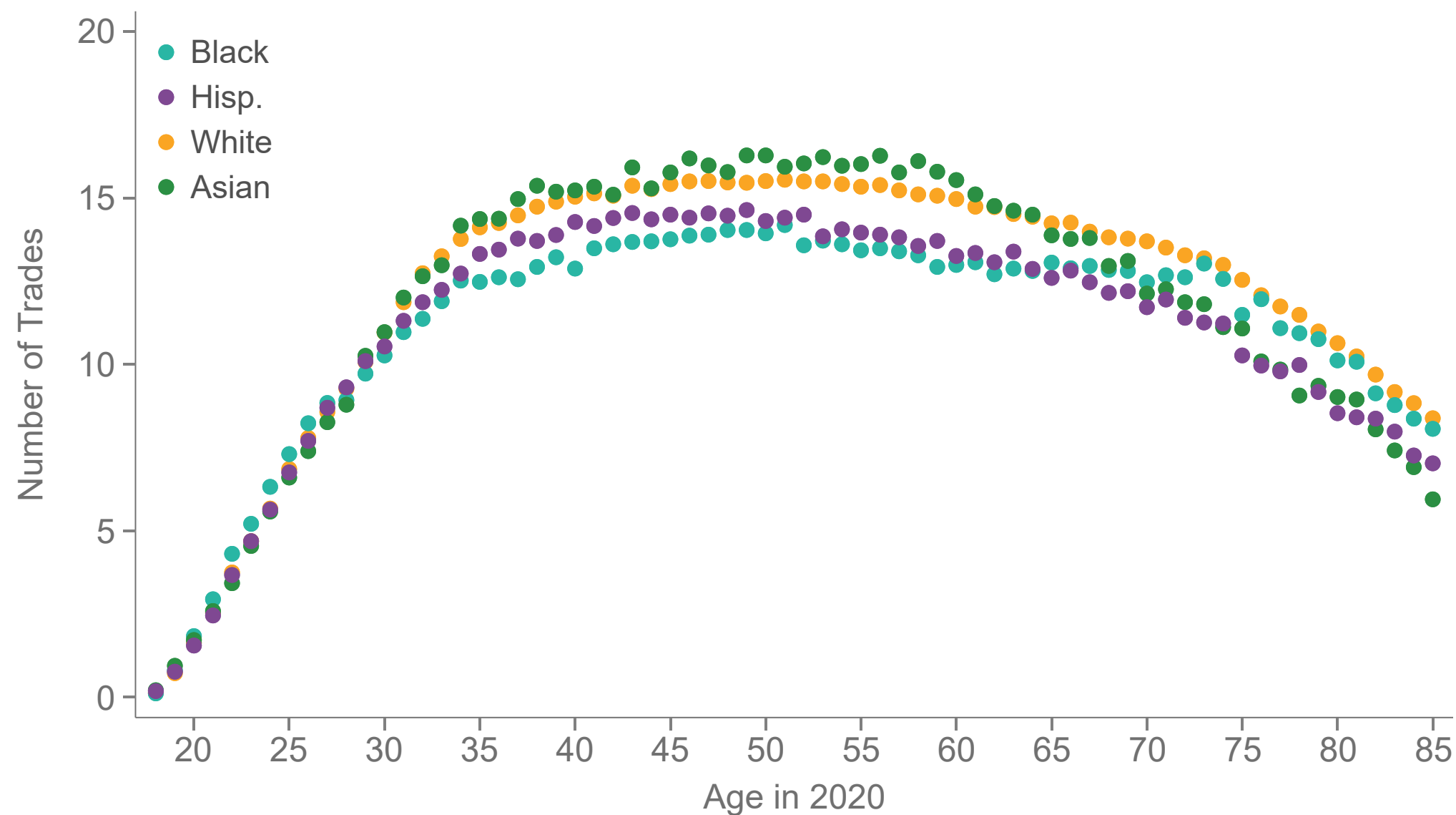
Number of Inquiries by Age



Credit Card Utilization Rate



Number of Tradelines by Age



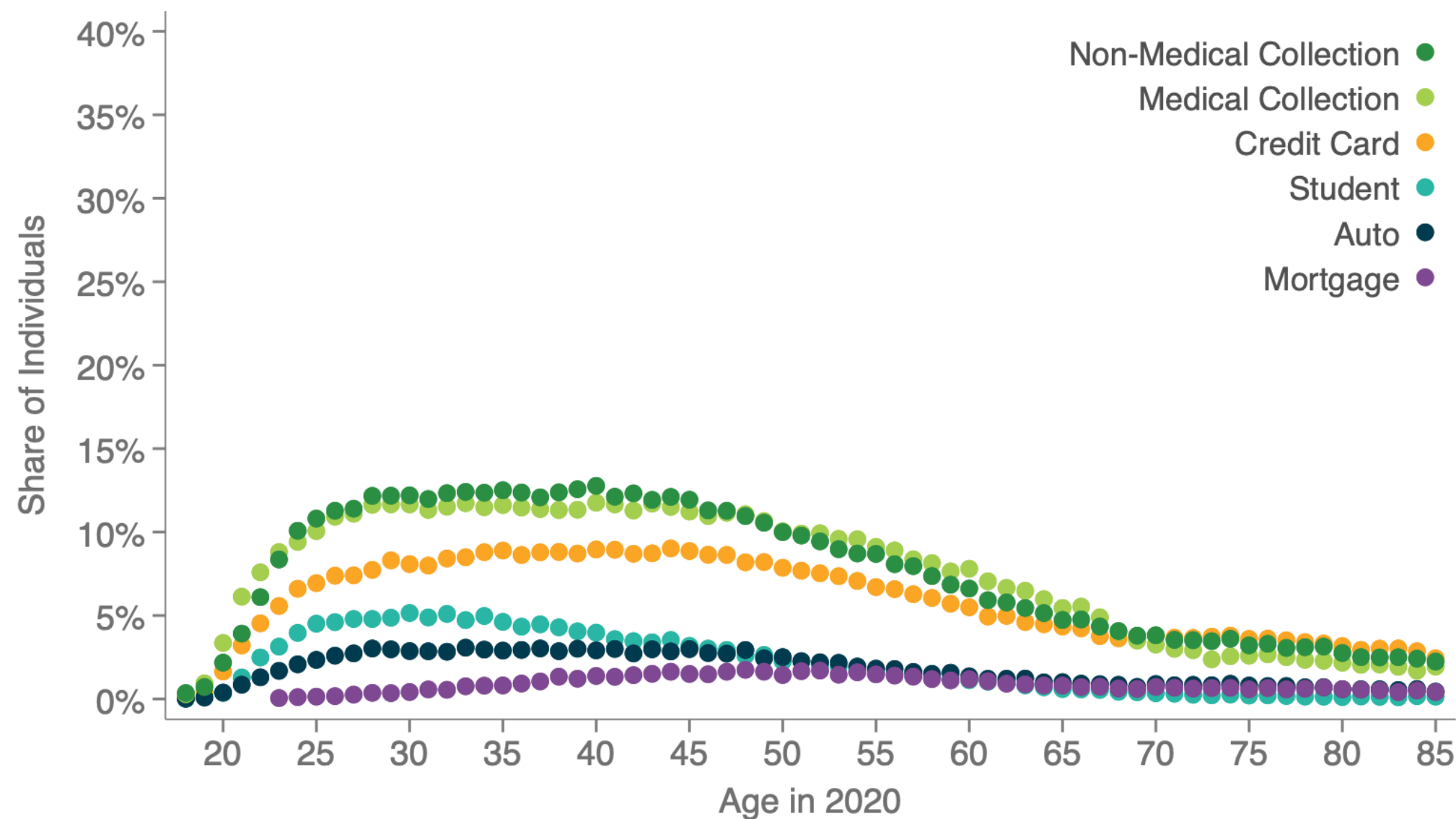
Ability to Come up with 2k vs. p25 White State Credit Score



Alternative Credit Use by Race, Class, and Geography (Prolific Survey)

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

90+ Day Late Payment Breakdown for White Individuals



Movers



Childhood Exposure Effects

- Let $\bar{y}_{pcs}$ denote average outcome in place c for parent income p , cohort s for those who do not move once
- Let $\Delta_{pods} = \bar{y}_{pds} - \bar{y}_{pos}$ the difference between origin and destination
- Regress adult outcome y_i for child who moved at age m from o to d

$$y_i = \sum_{m=-6}^{35} I(m_i = m) \beta_m \Delta_{odps} + \text{Controls} + \varepsilon_i$$

- Controls include:
 - Age at move, parent income rank, average outcomes children from origin (y_{pos}), cohort-varying intercepts
- Coefficient $\beta_{m-1} - \beta_m$ captures exposure effect of spending year m in place with one unit higher outcome



Childhood Exposure Effects

$$y_i = \sum_{m=-6}^{35} I(m_i = m) \beta_m \Delta_{odps} + \text{Controls} + \varepsilon_i$$

$$\begin{aligned} \text{Controls} = & \sum_{s=1982}^{1985} I(s_i = s) [\beta_s \Delta_{odps} + \zeta_s p_i + \alpha_s + \phi_s \bar{y}_{ops}] \\ & + \sum_{m=-6}^{35} I(m_i = m) [\alpha_m + \phi_m \bar{y}_{ops} + \zeta_m p_i] \end{aligned}$$

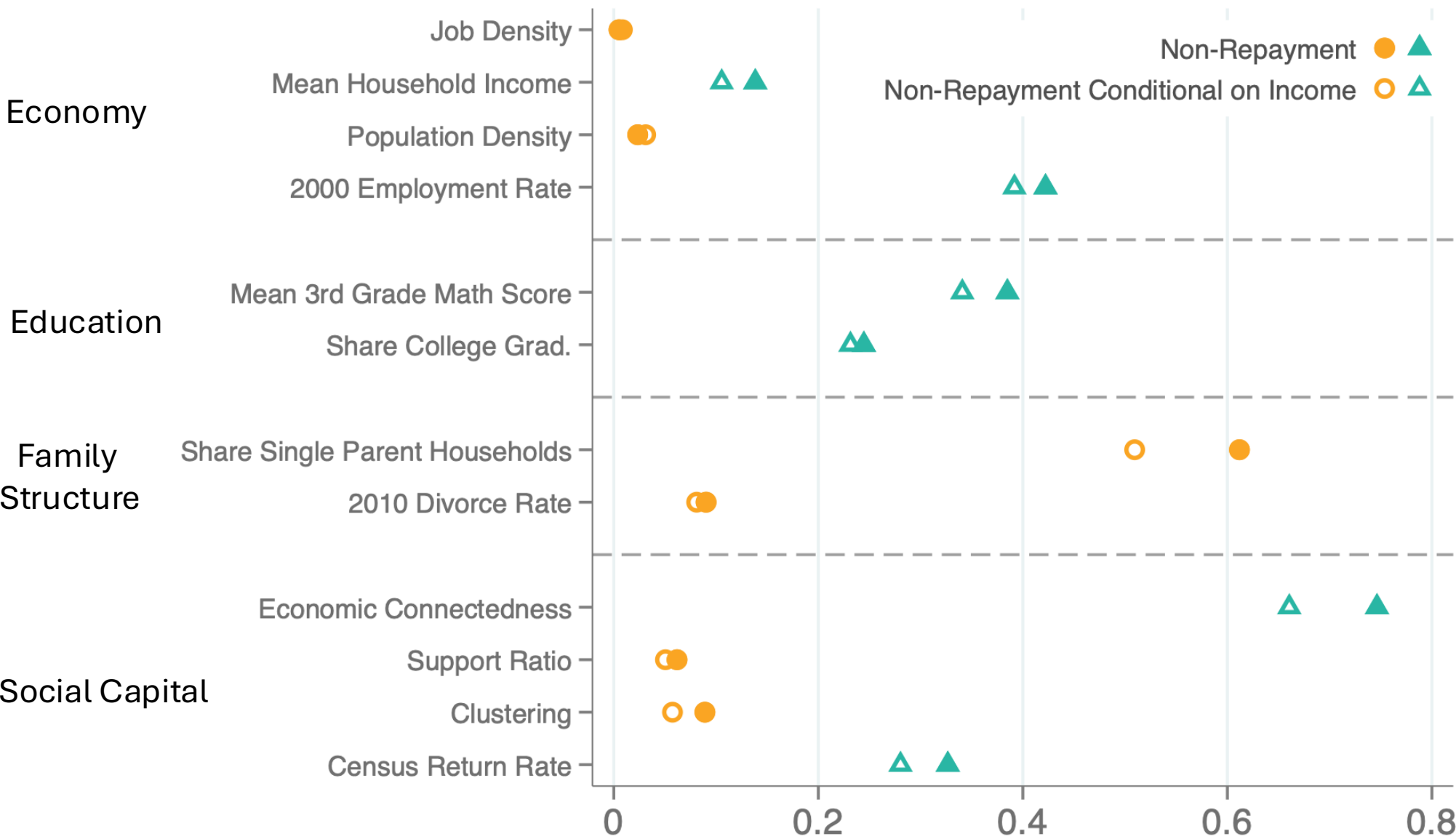


Childhood Exposure Effects for Repayment in 2004 (age 19-22)

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



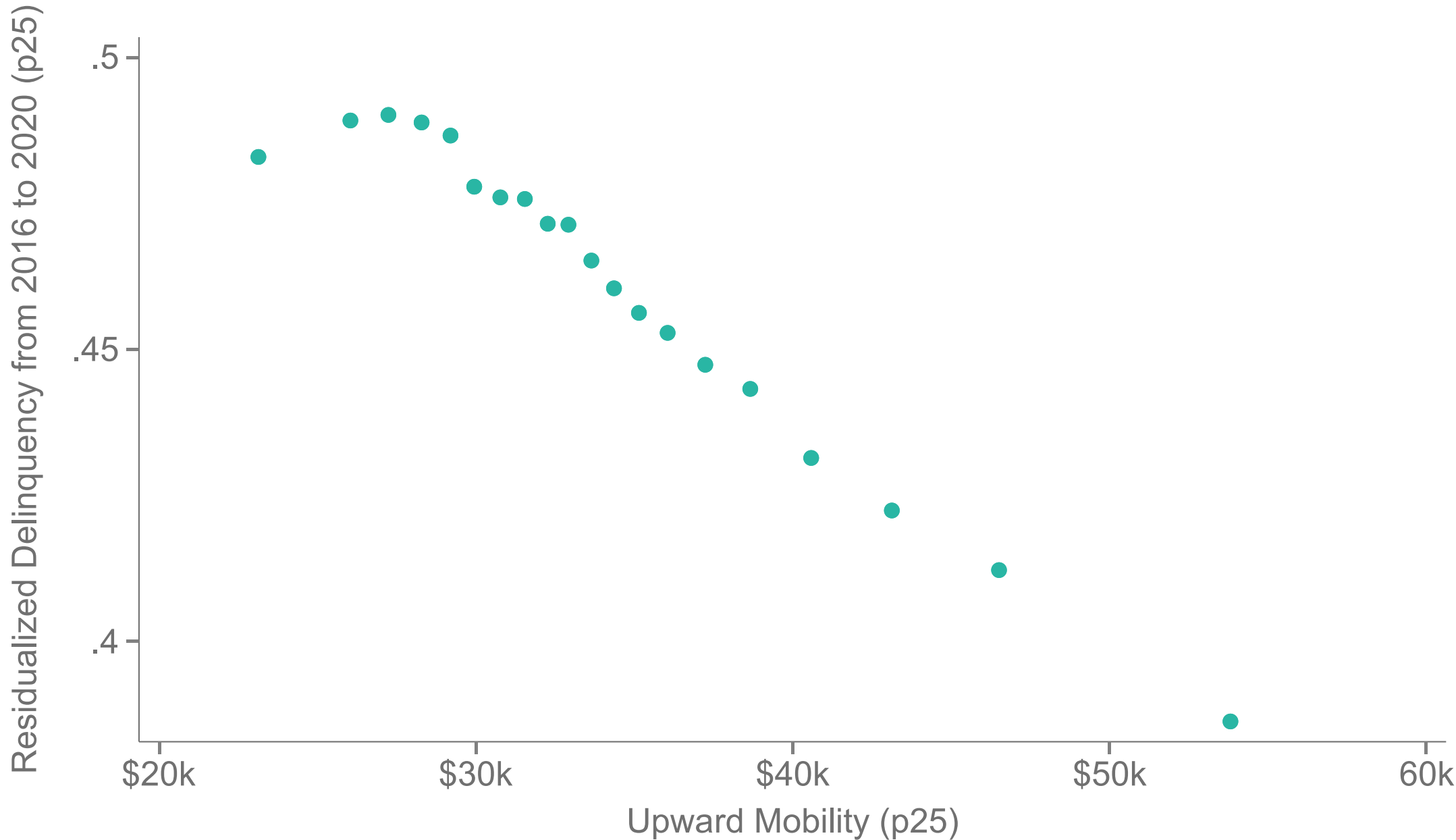
What Types of Places Produce Children With Higher Future Repayment?



What Types of Places Produce Children With Higher Future Income?



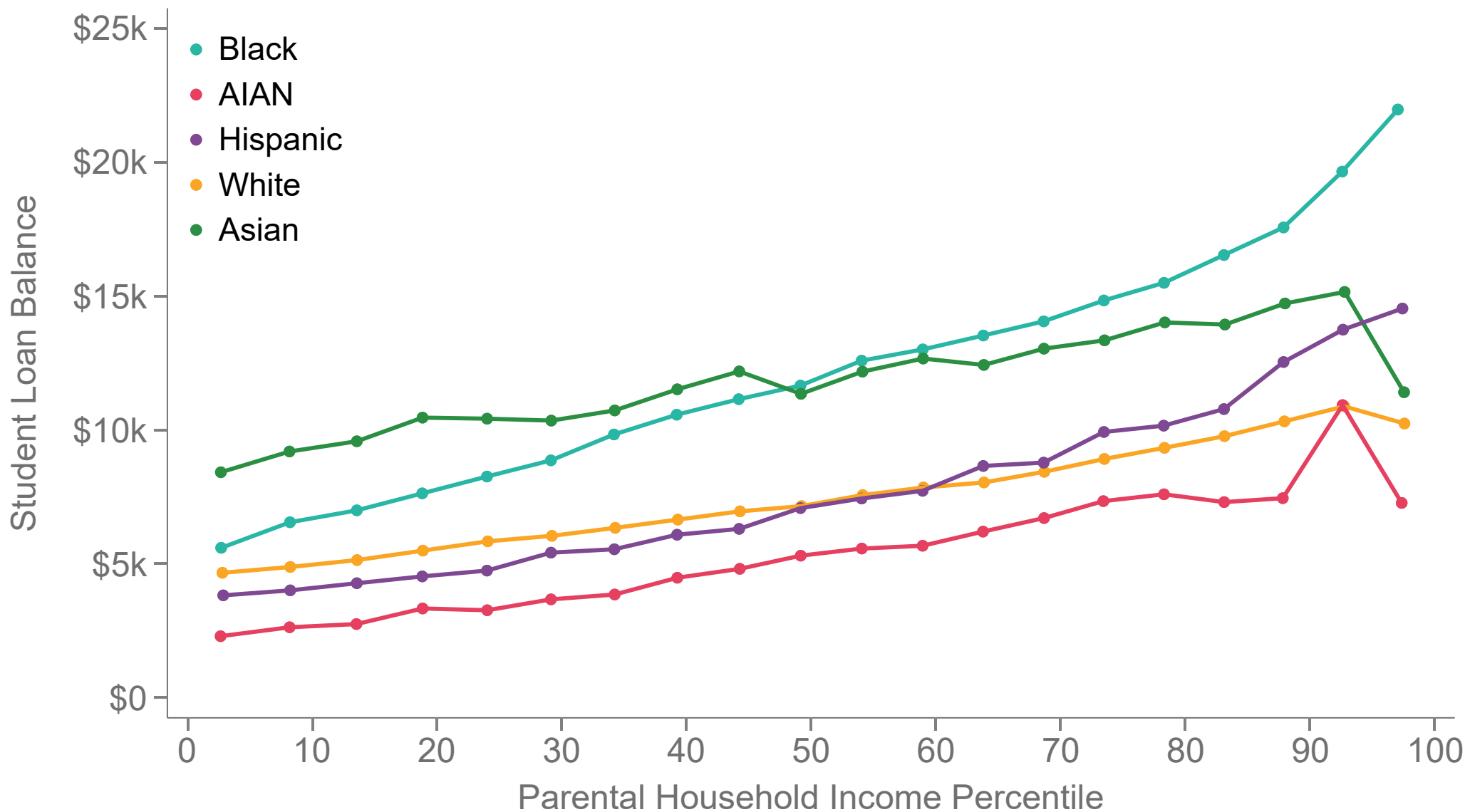
Upward Income Mobility versus Repayment Conditional on Income (White)



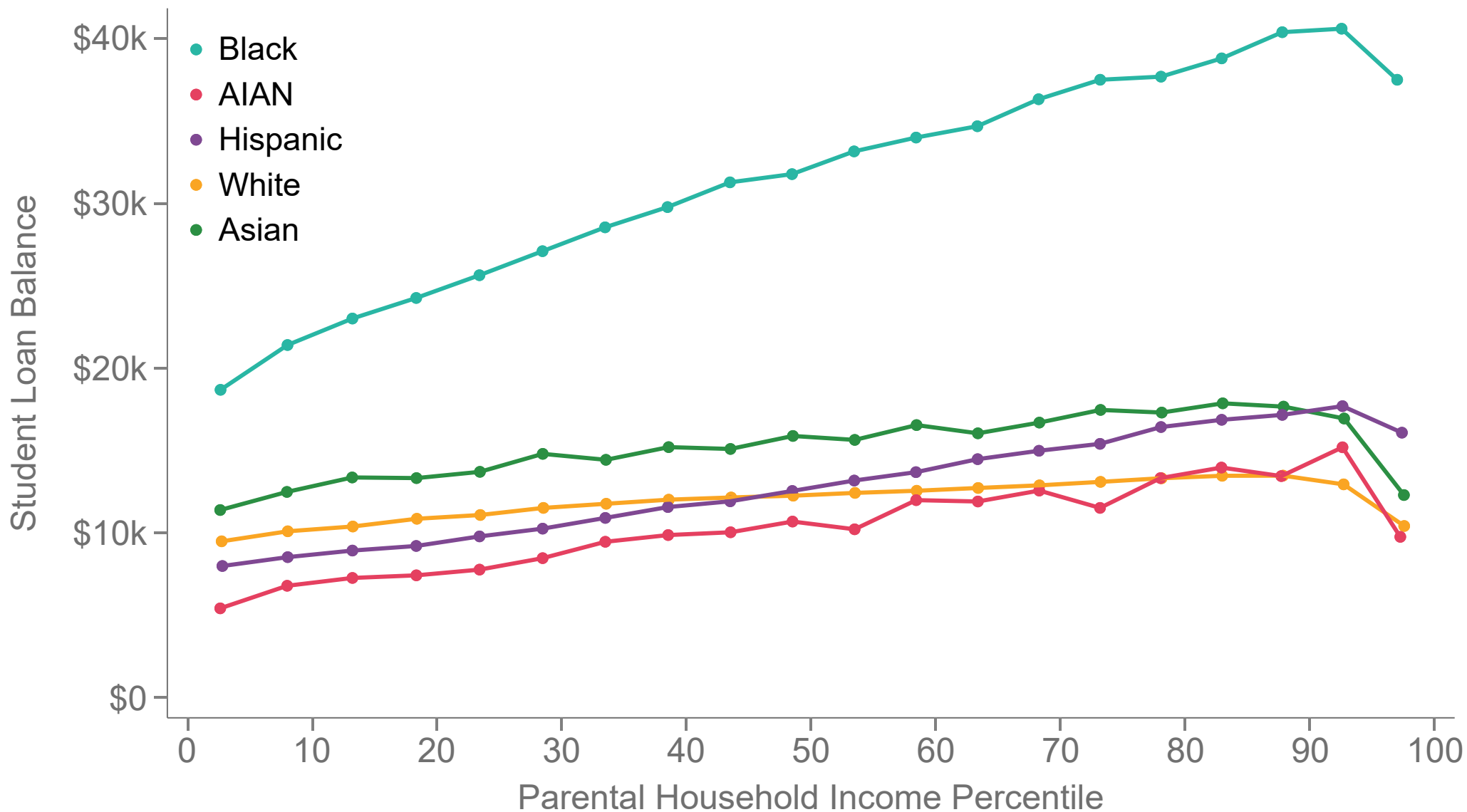
The Rise of Student Loans



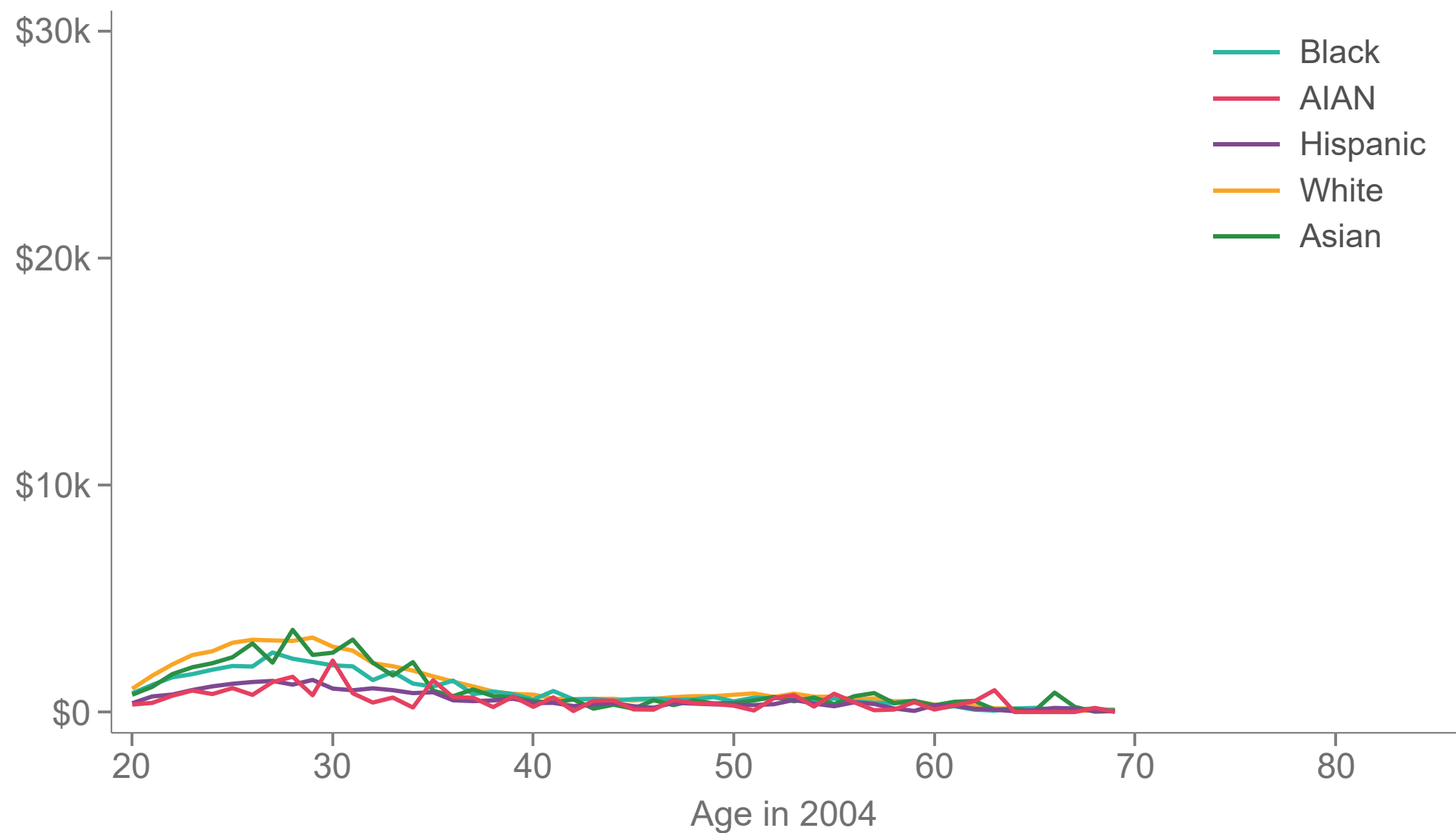
Student Loan Balances in 2020 by Parent Income and Race (Male)



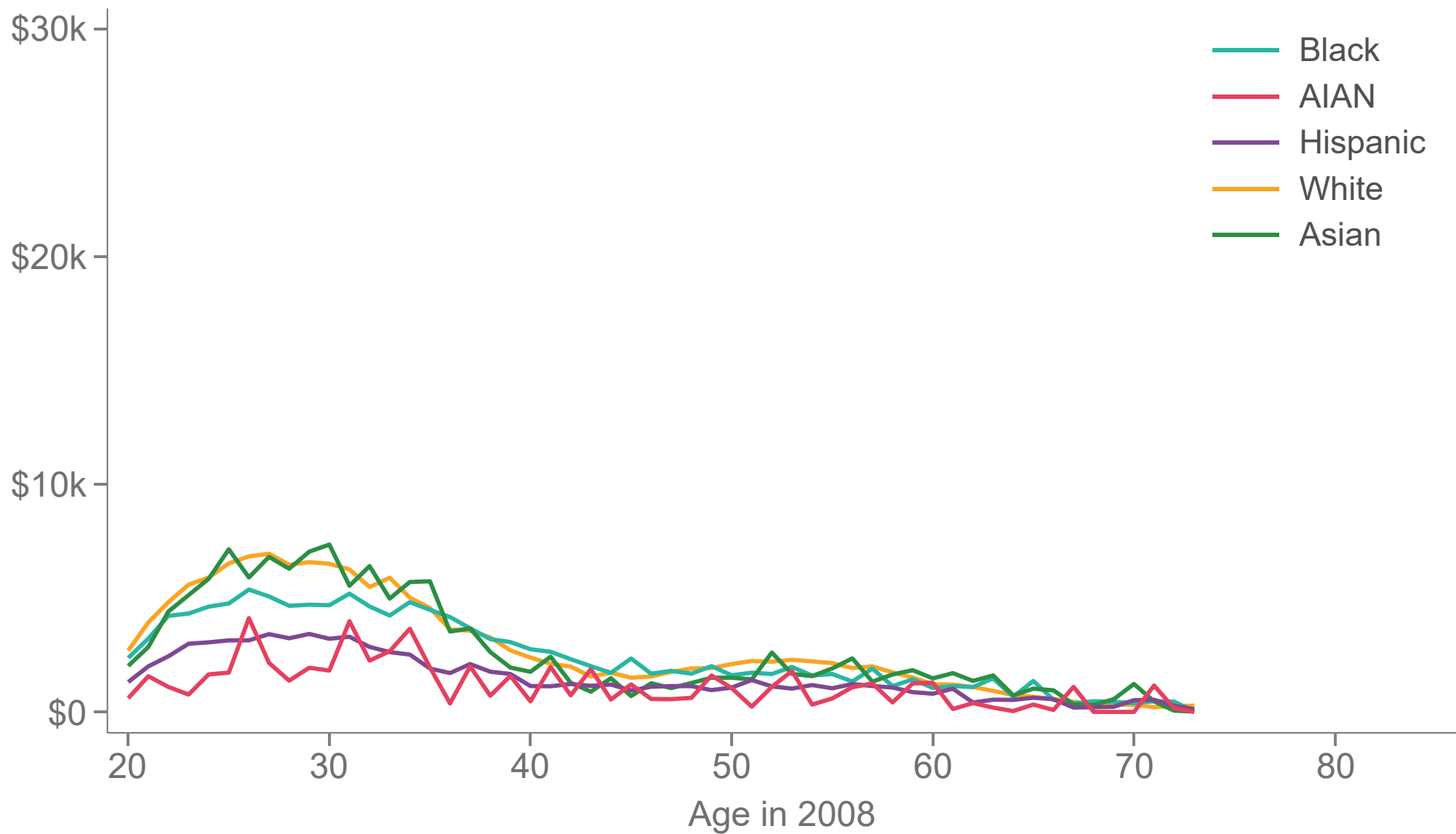
Student Loan Balances in 2020 by Parent Income and Race (Female)



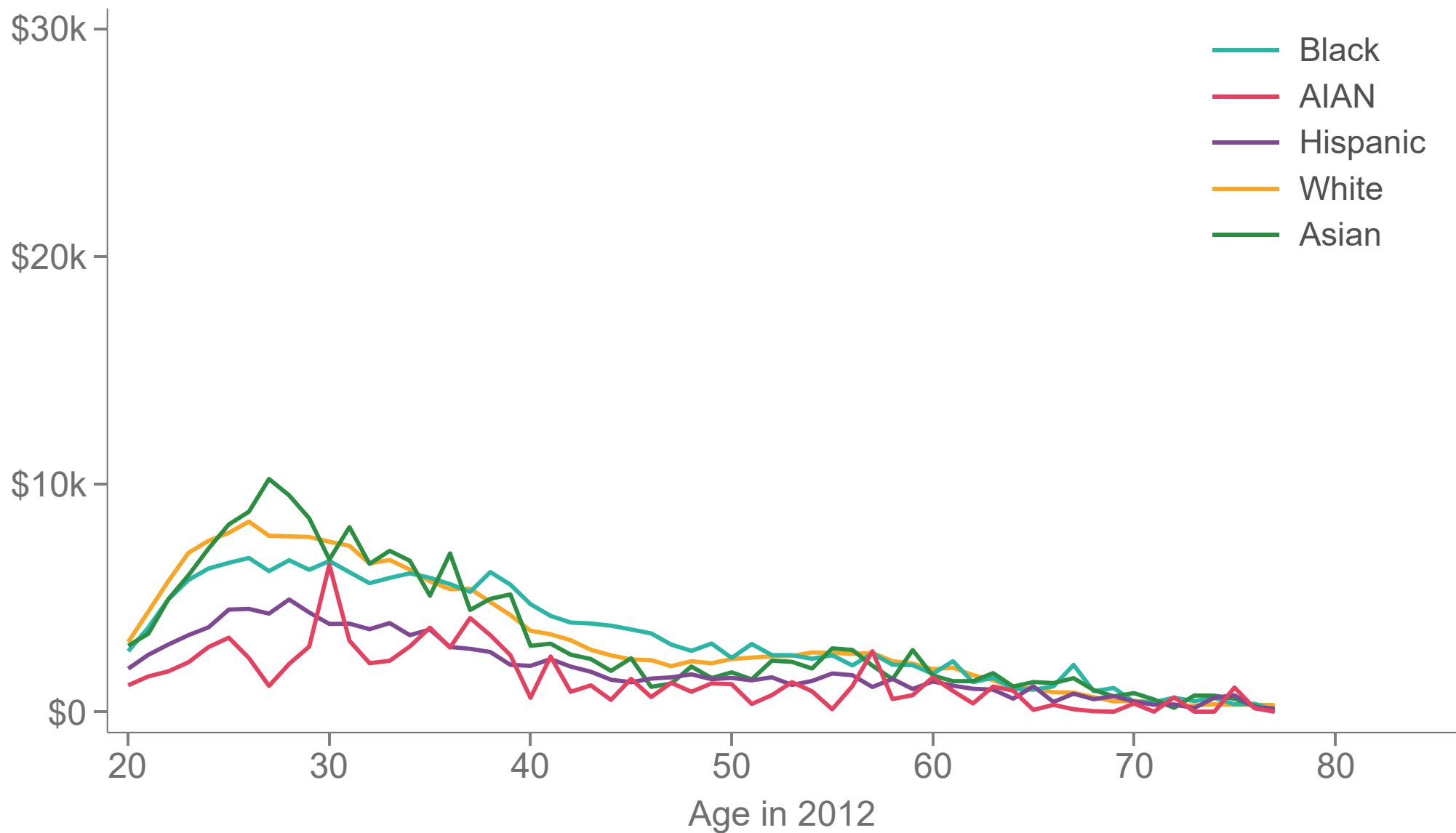
Student Loan Balances for Males, by Age and Race in 2004



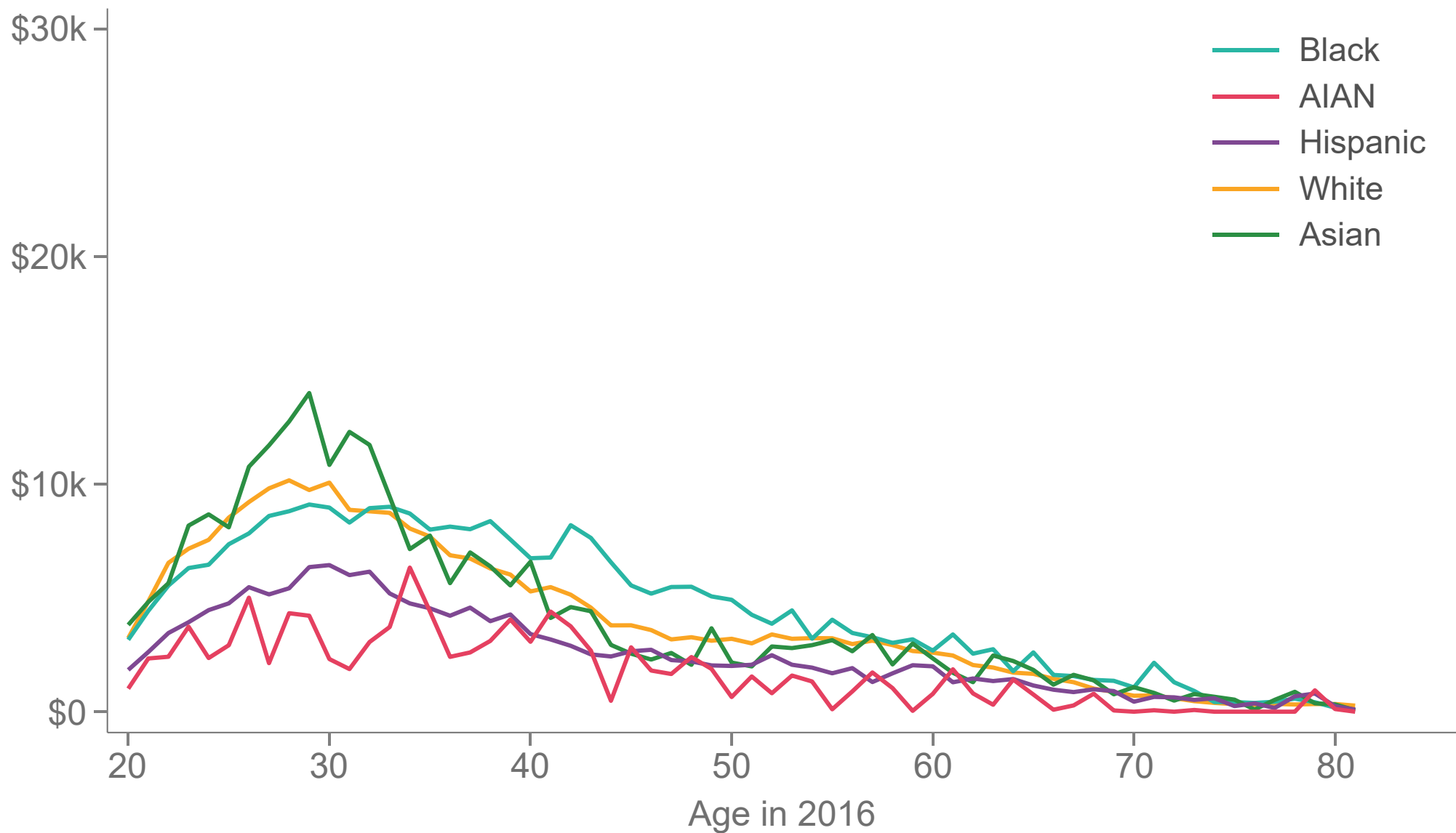
Student Loan Balances for Males, by Age and Race in 2008



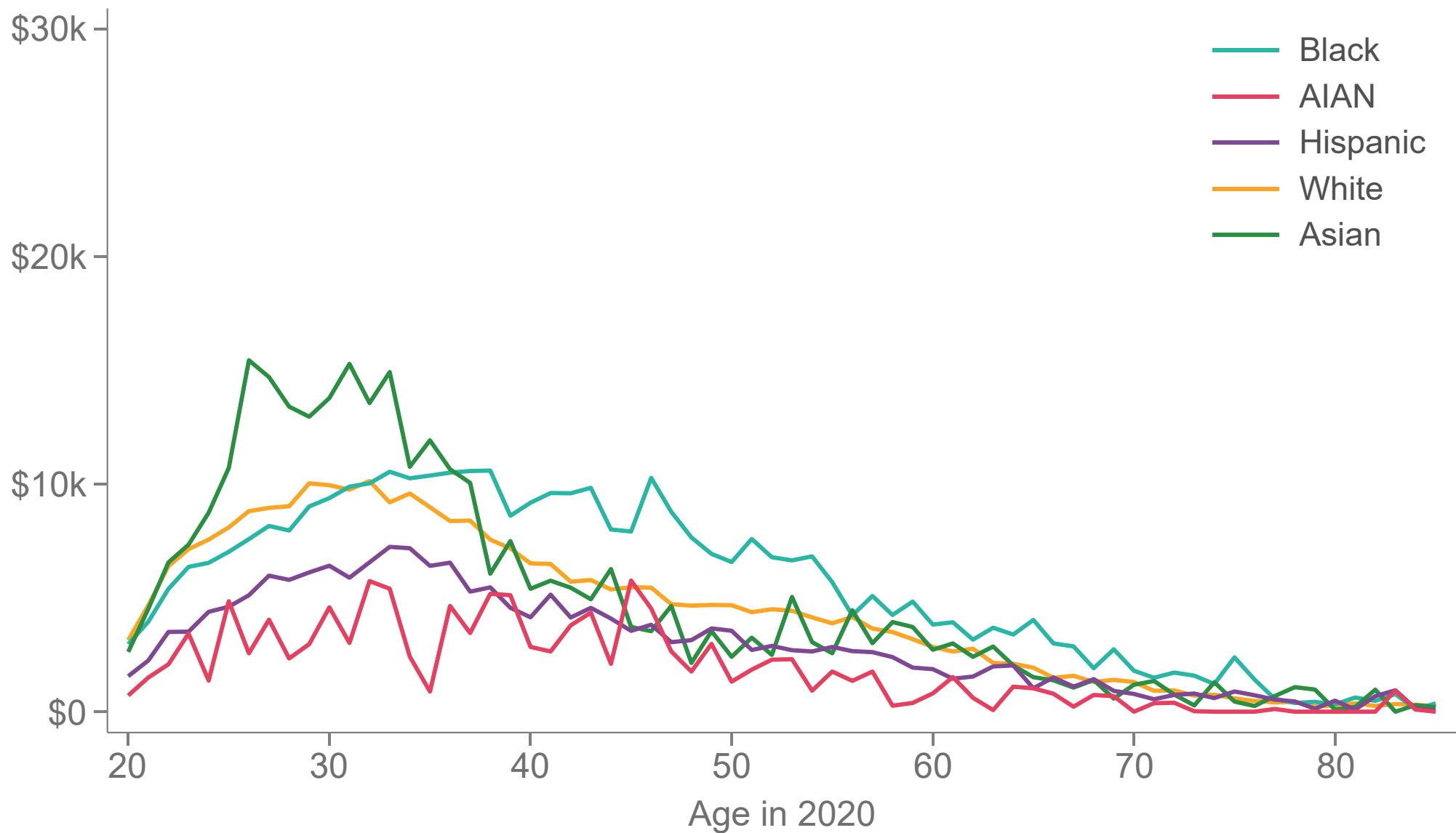
Student Loan Balances for Males, by Age and Race in 2012



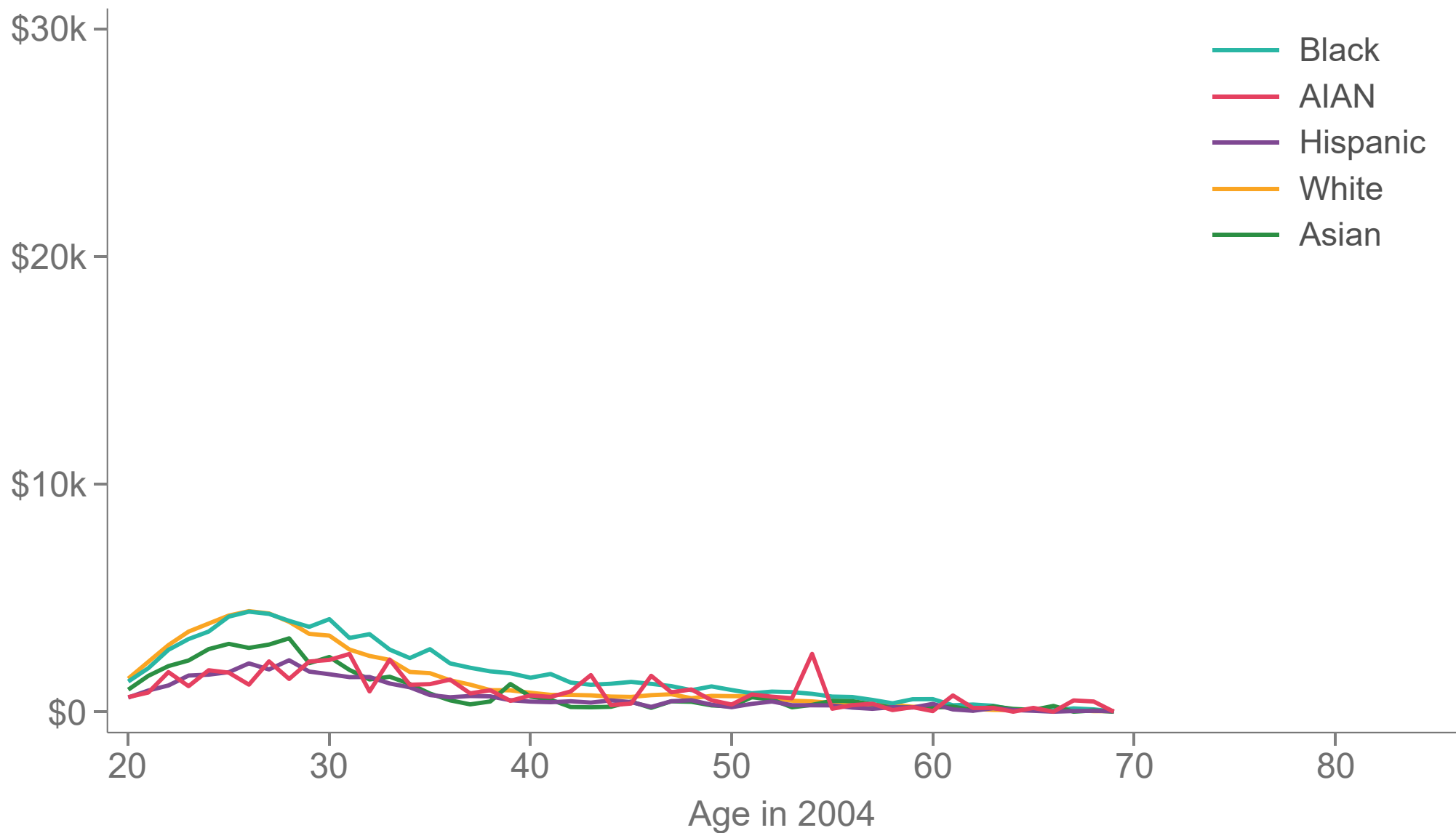
Student Loan Balances for Males, by Age and Race in 2016



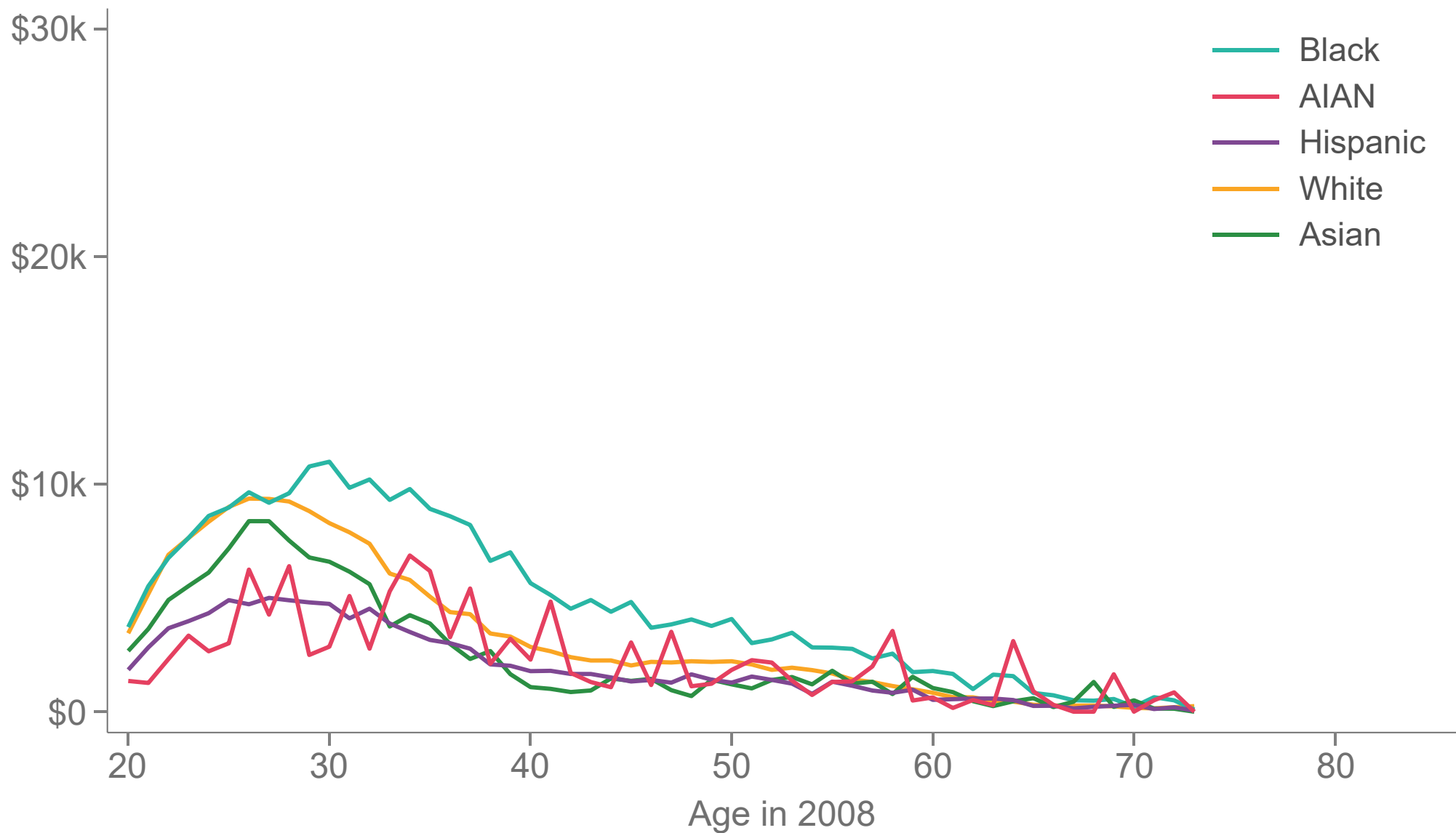
Student Loan Balances for Males, by Age and Race in 2020



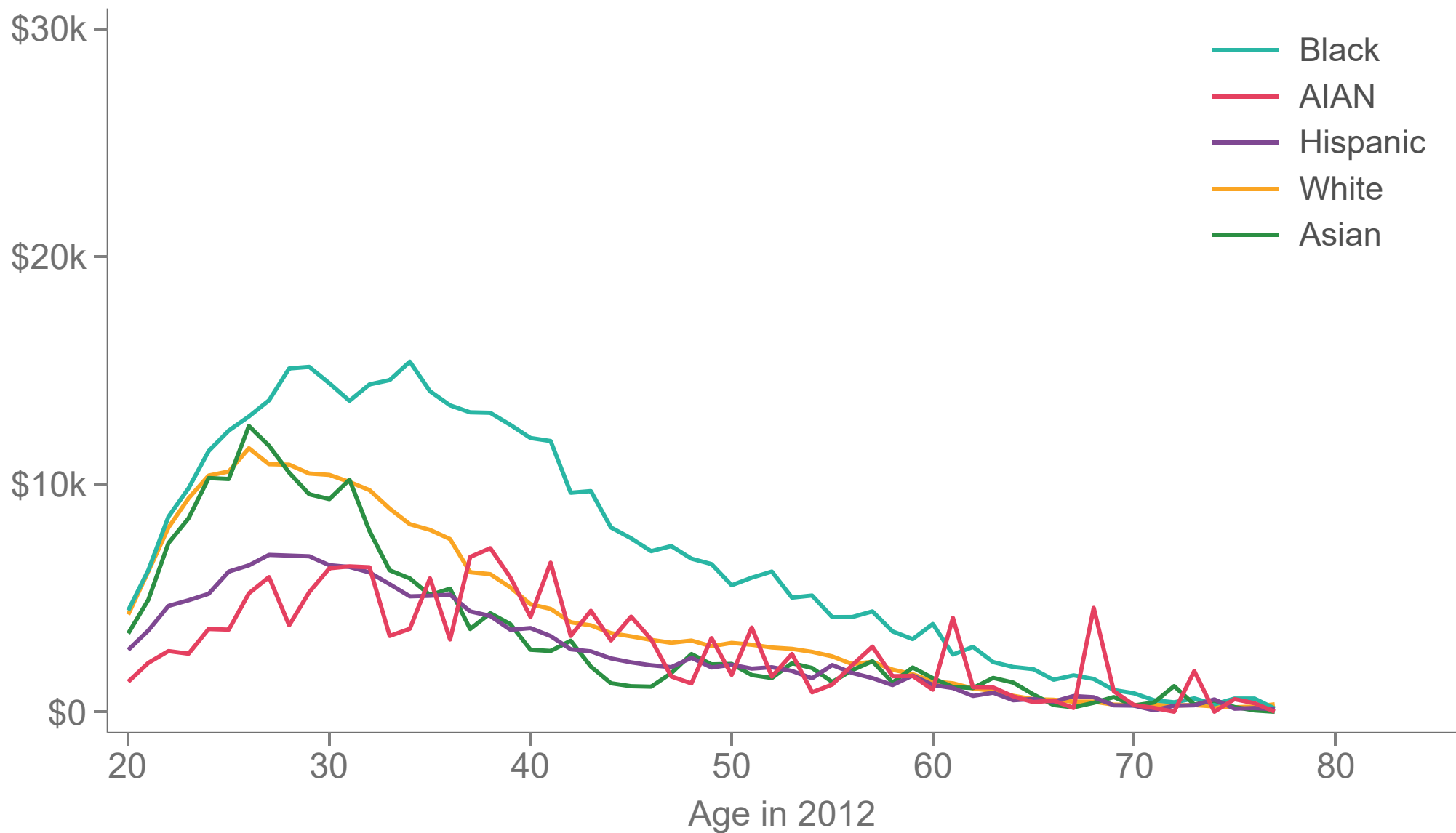
Student Loan Balances for Females, by Age and Race in 2004



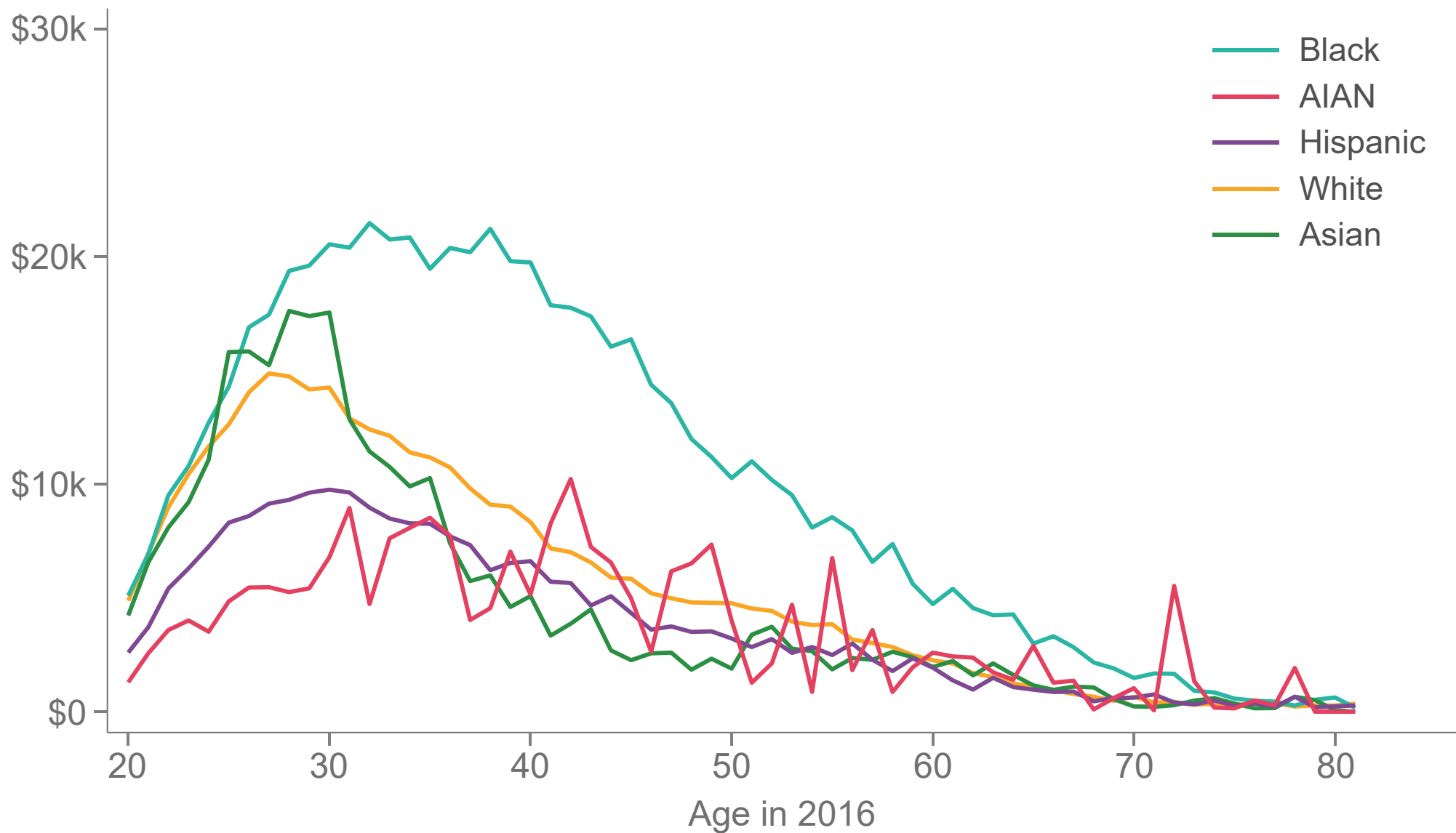
Student Loan Balances for Females, by Age and Race in 2008



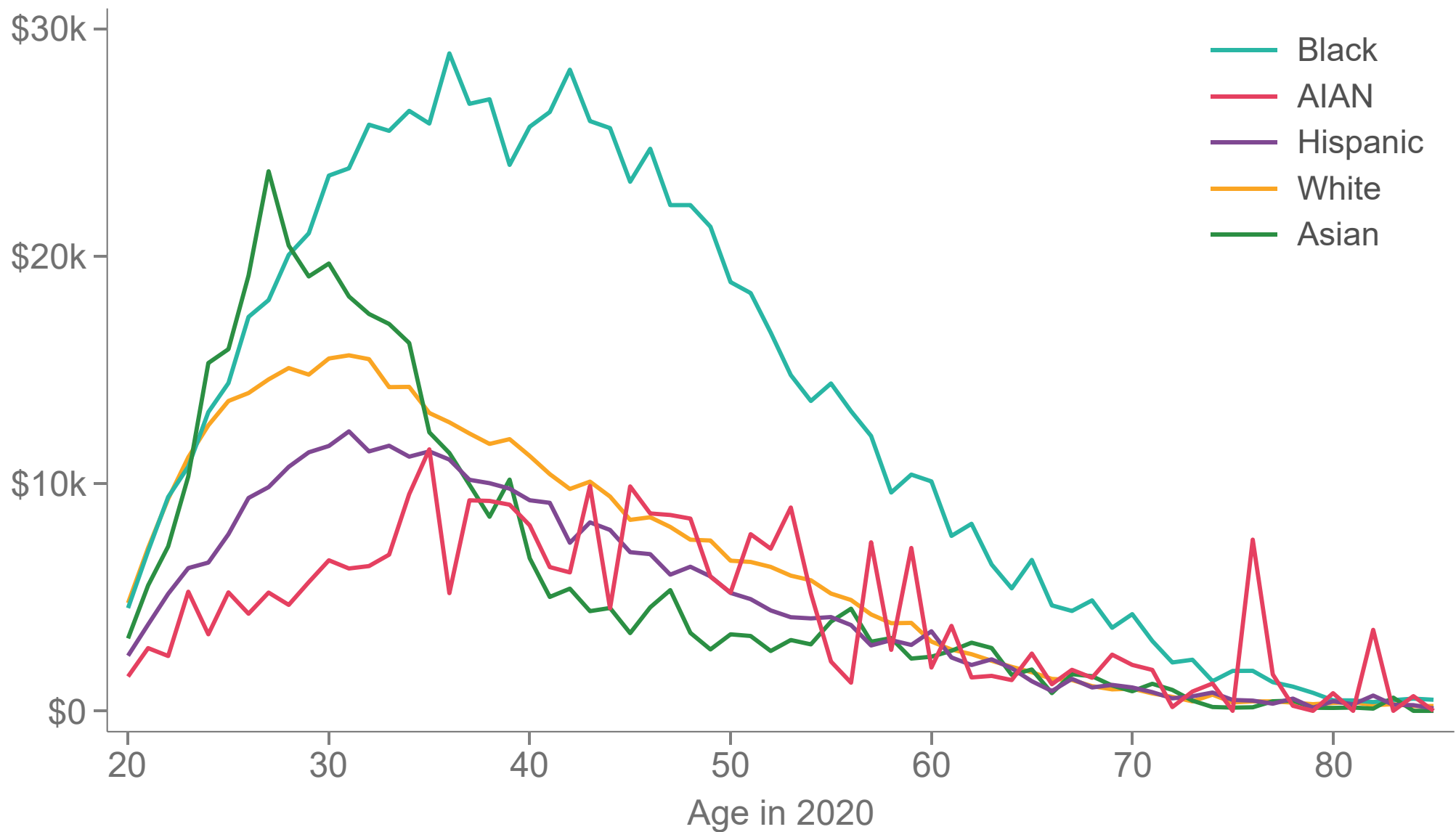
Student Loan Balances for Females, by Age and Race in 2012



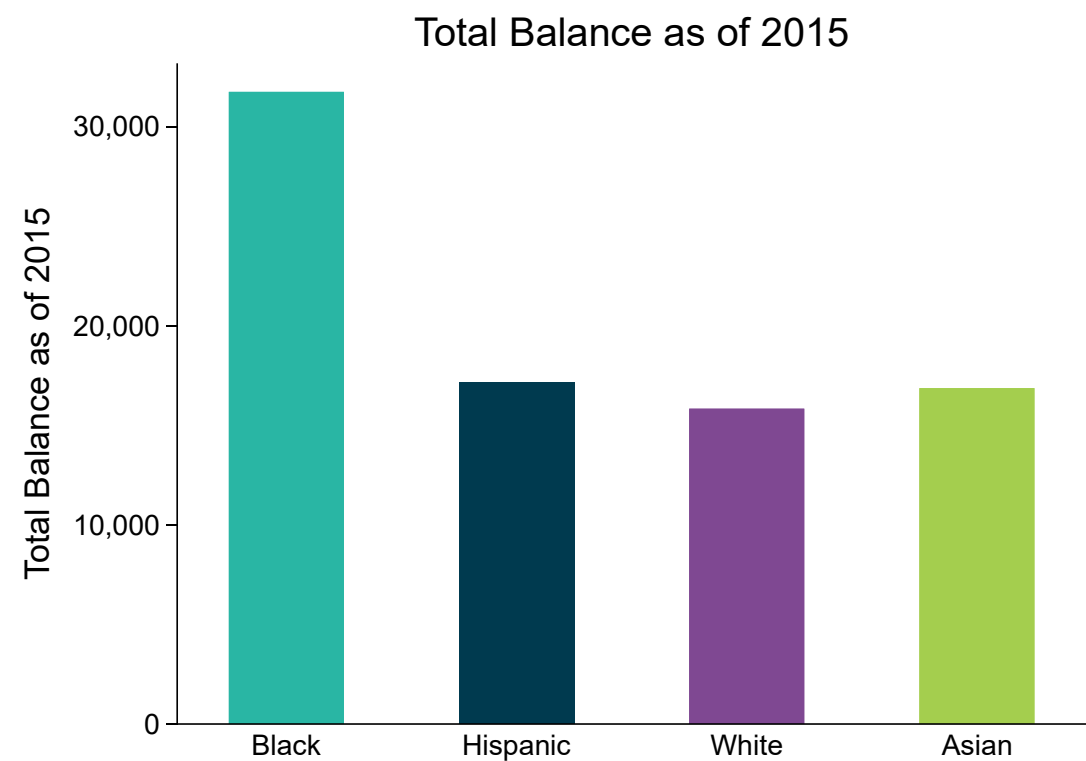
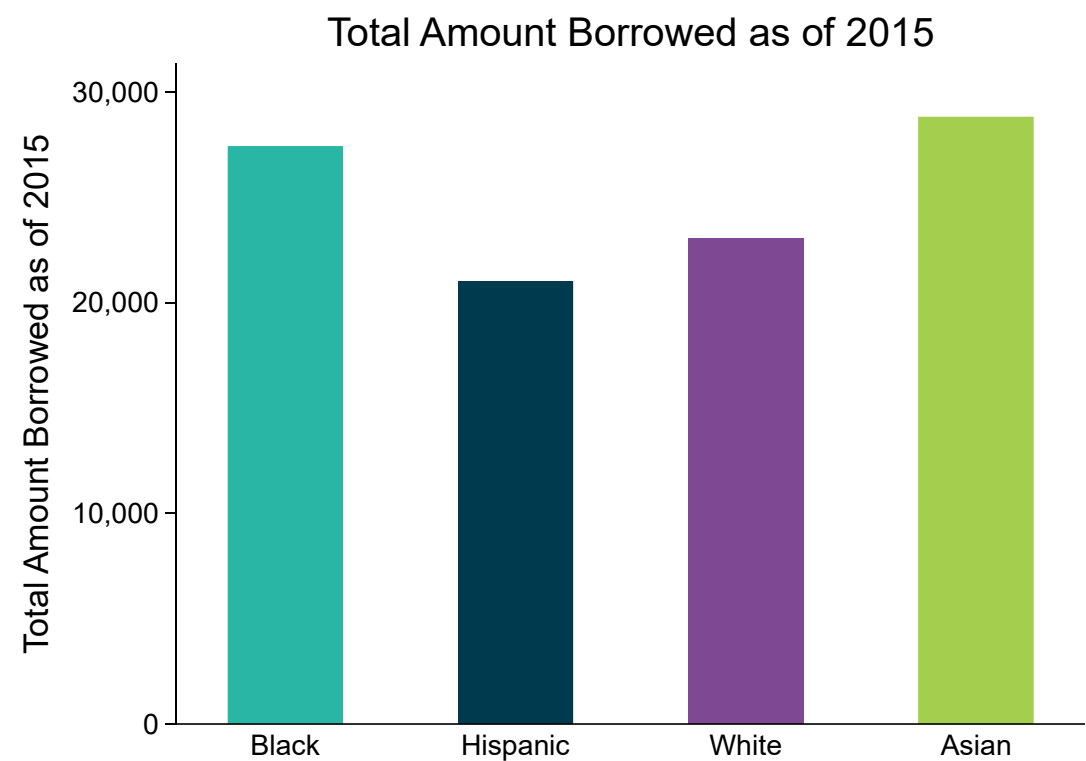
Student Loan Balances for Females, by Age and Race in 2016



Student Loan Balances for Females, by Age and Race in 2020



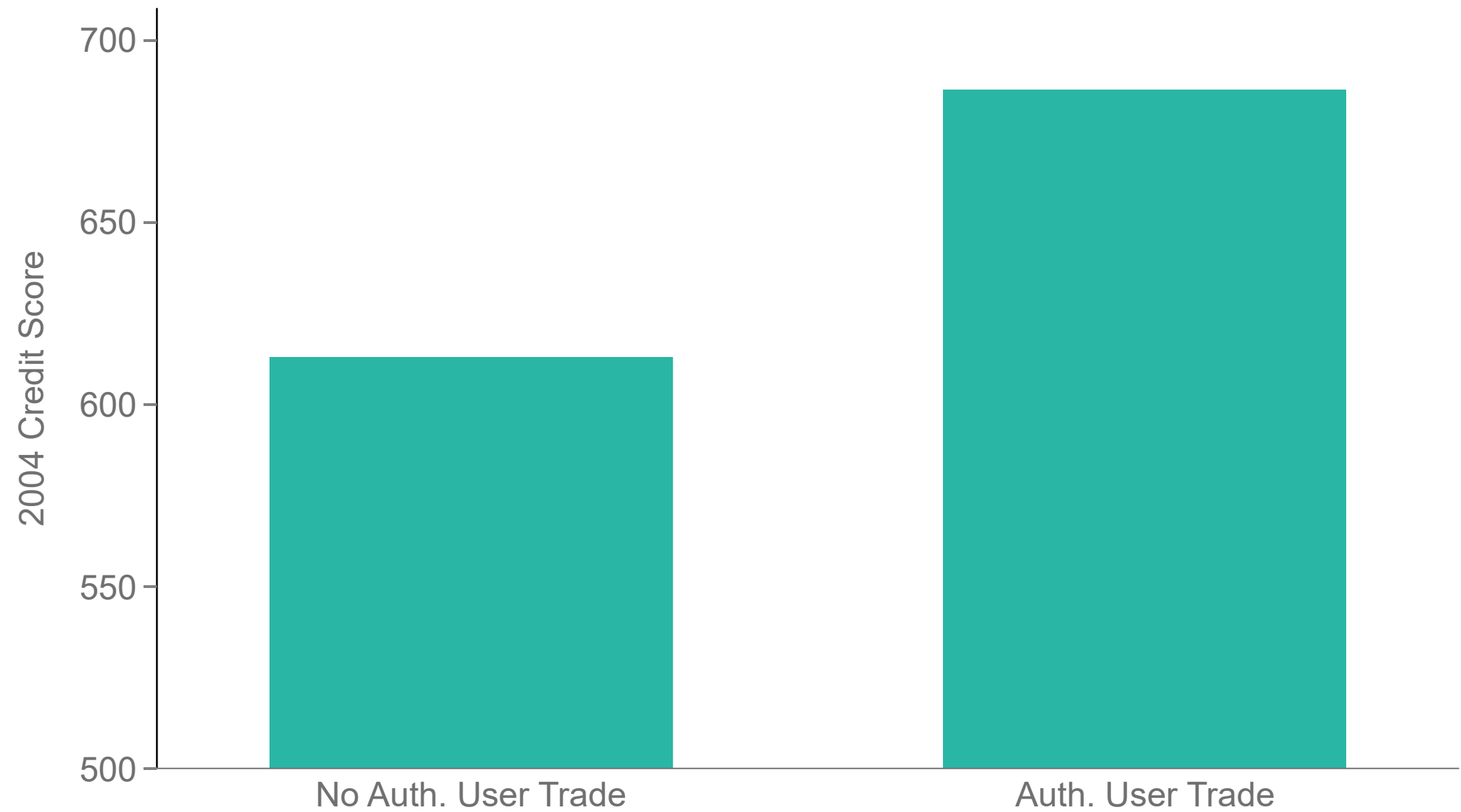
Balances vs. Amount Borrowed Amongst Borrowers?



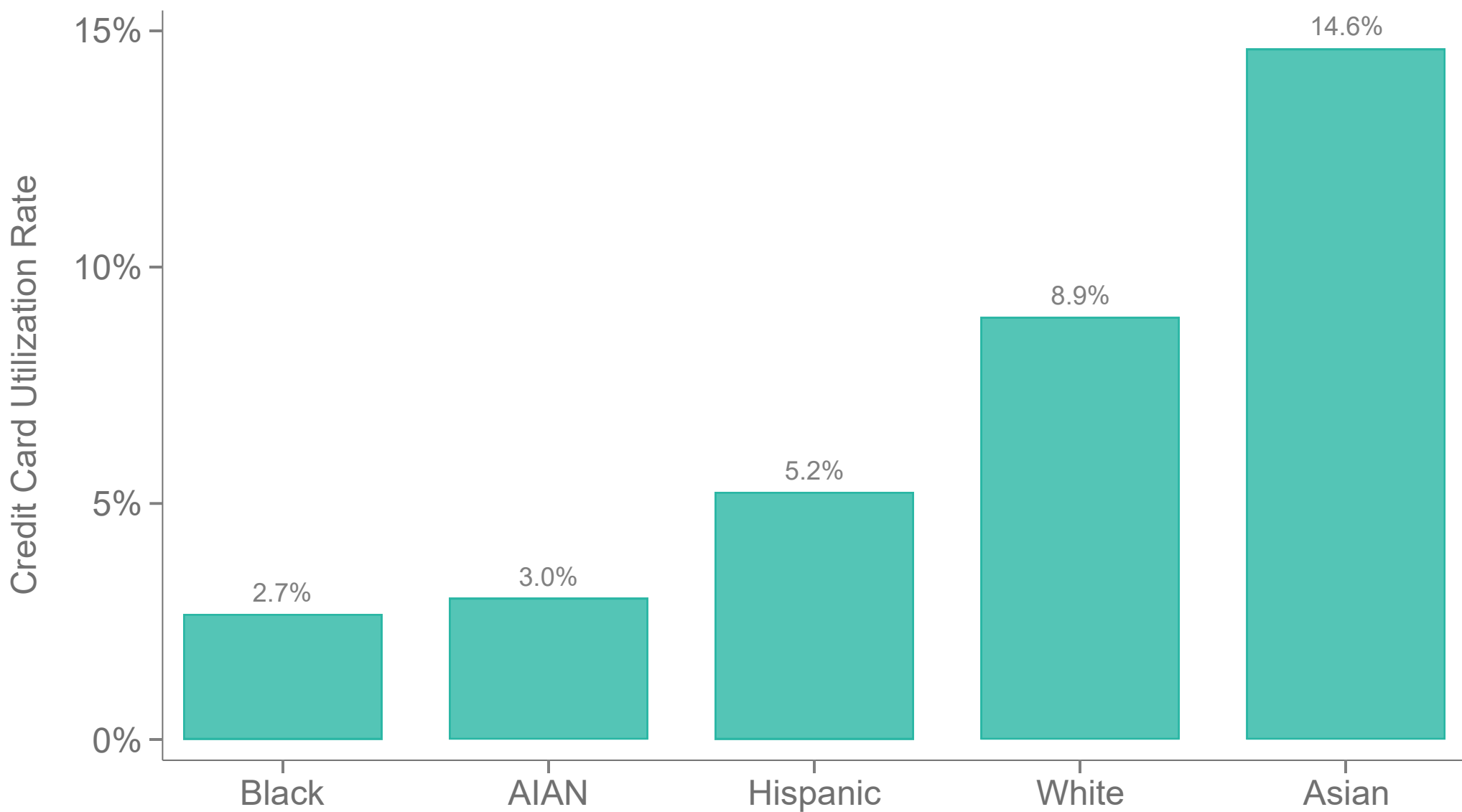
Authorized Users



Being on Your Parent's Credit Card Acct. Boosts Child Credit Score at Age 19



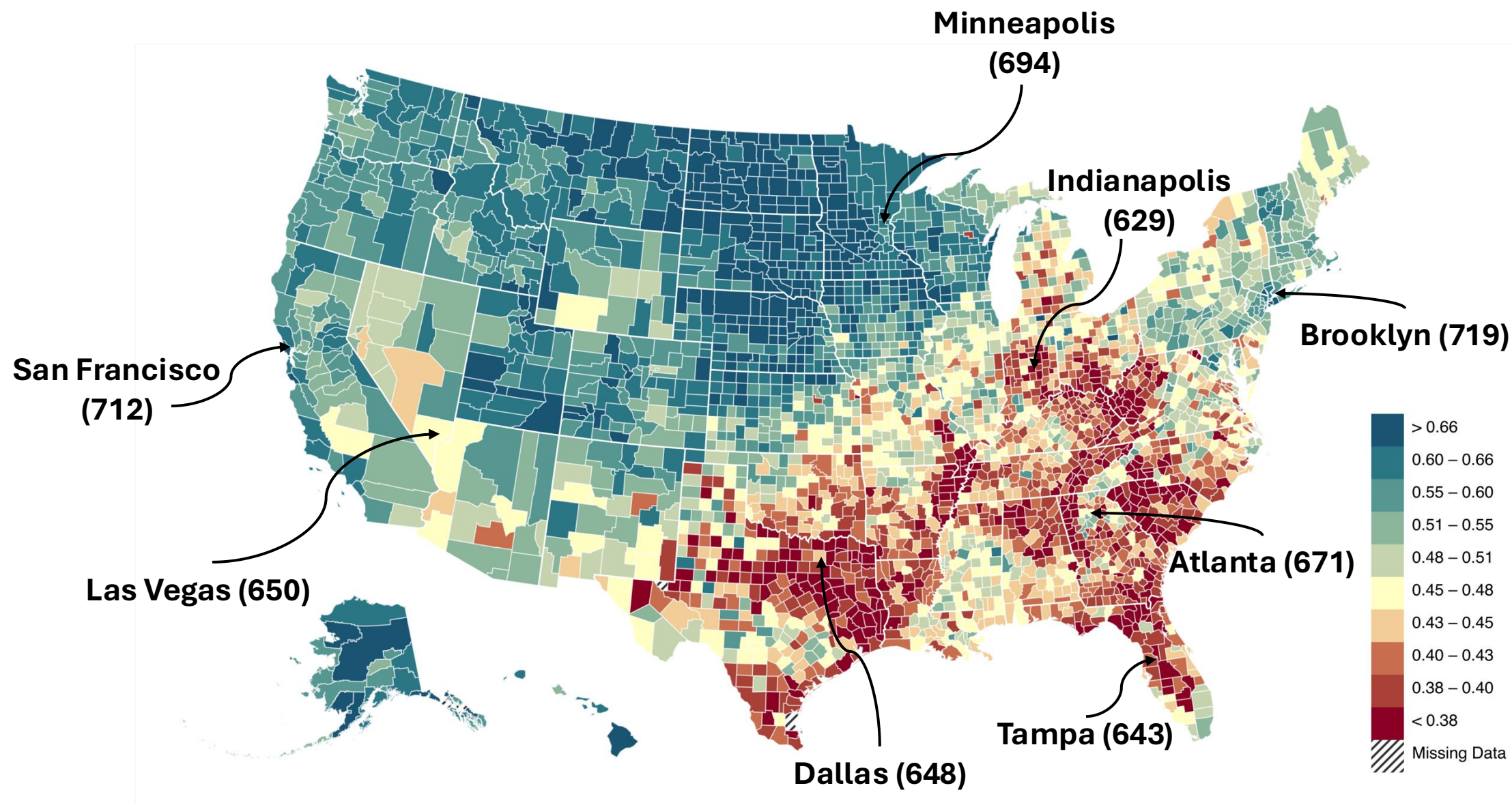
Race Gaps in Auth. User Trades Correlate With Racial Credit Score Gaps



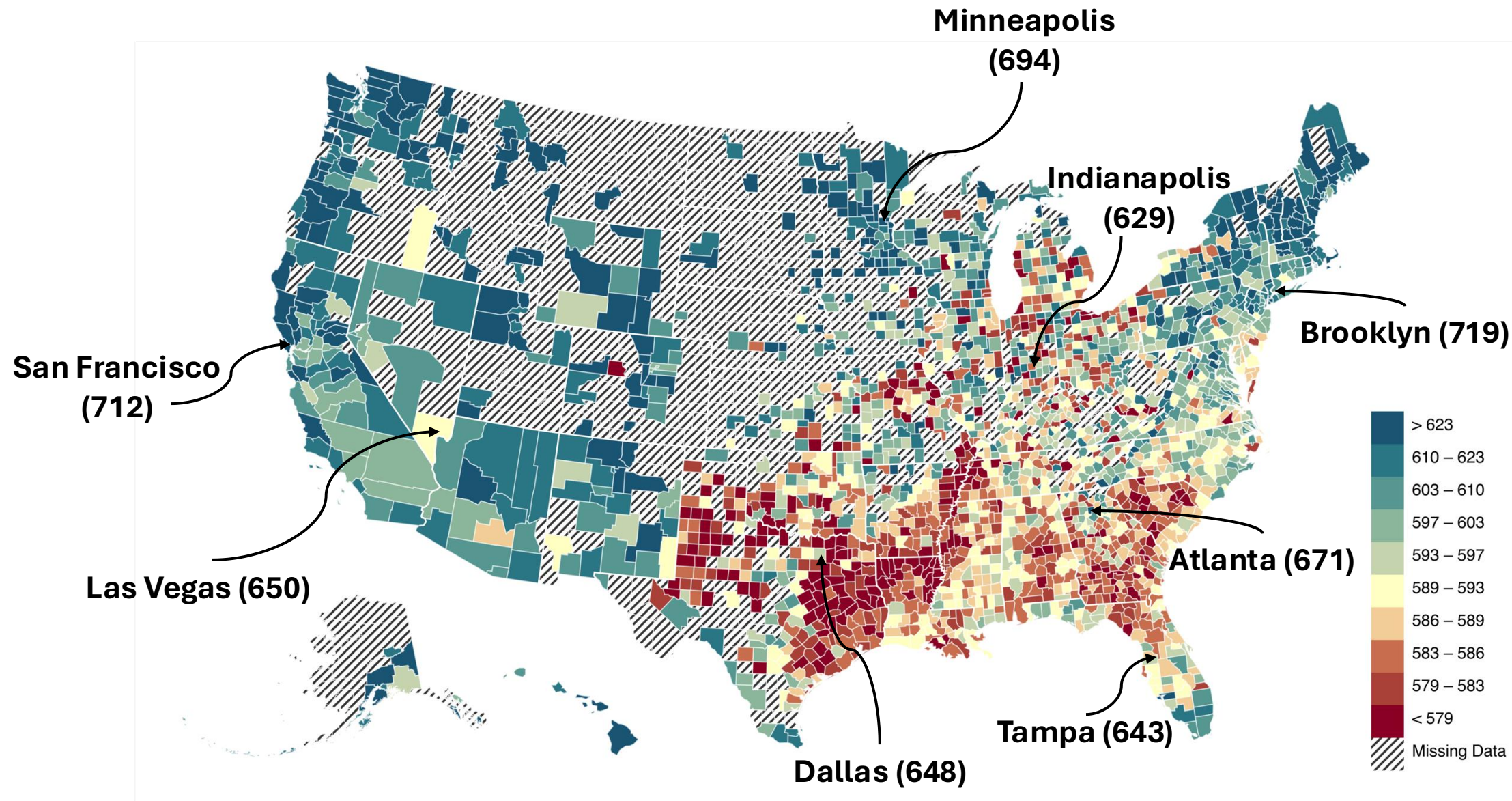
Other Maps



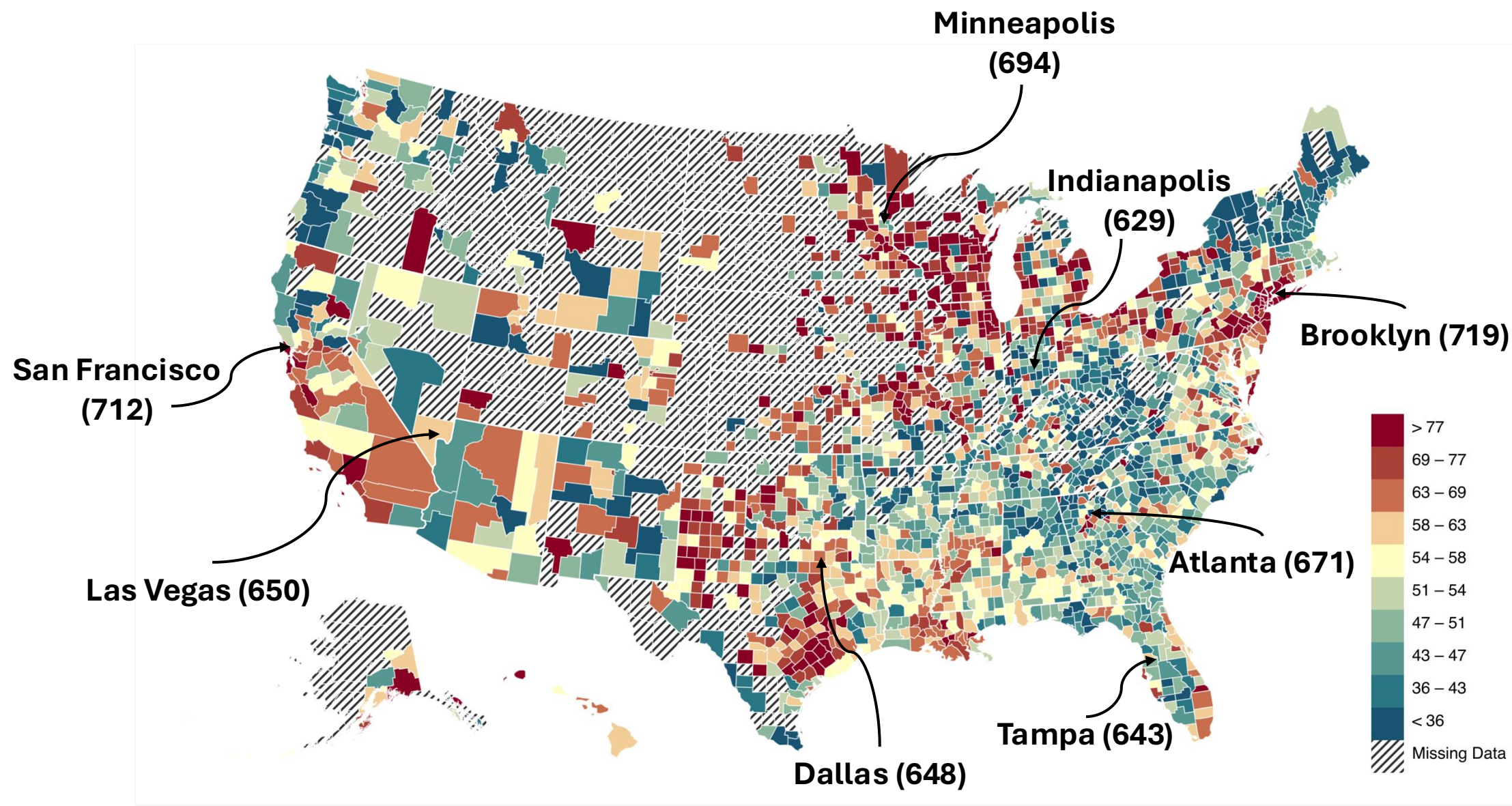
Repayment by County for White Individuals From Low-Income (p25) Families



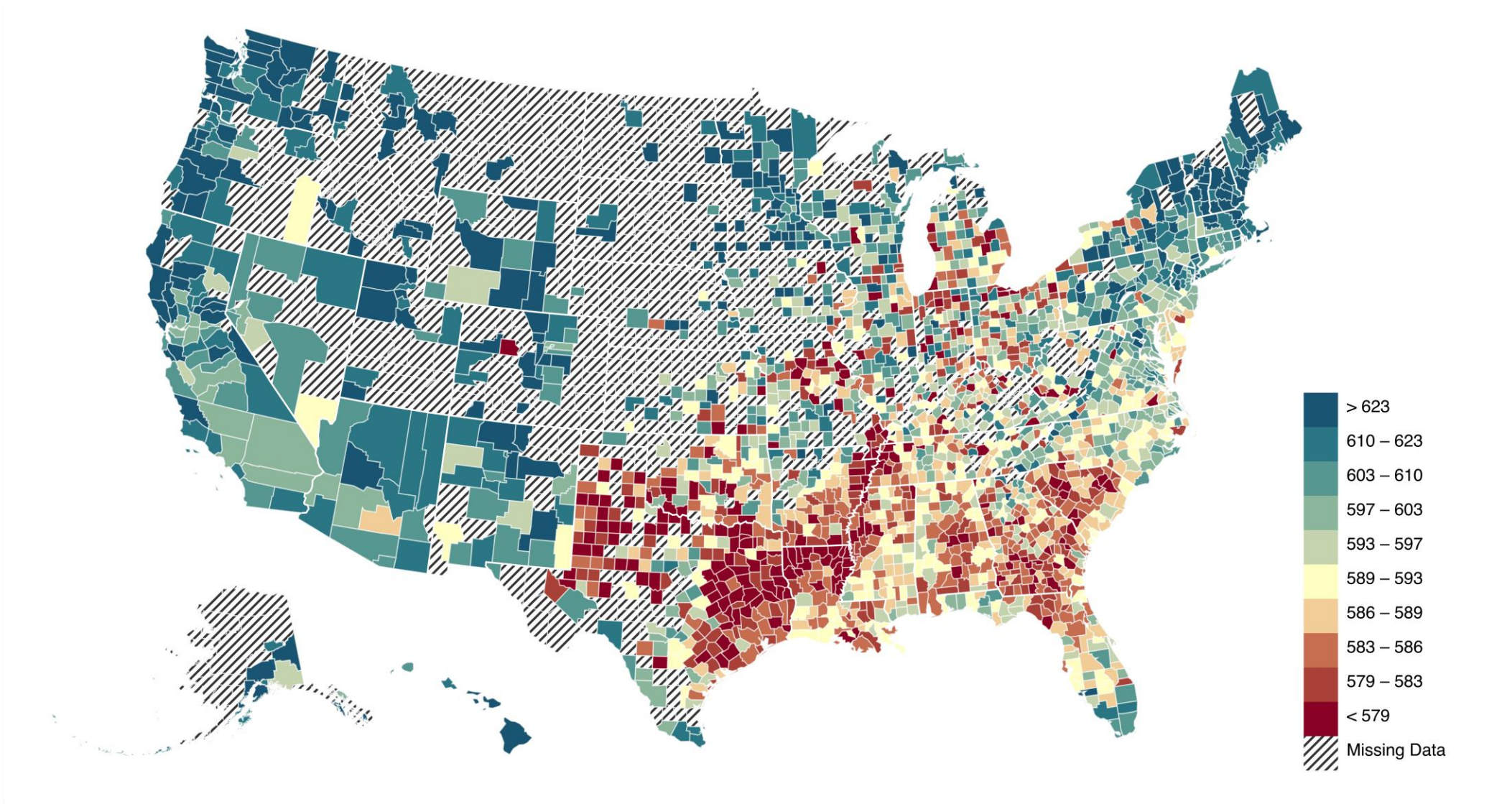
Credit Scores by County for Black Individuals From Low-Income (p25) Families



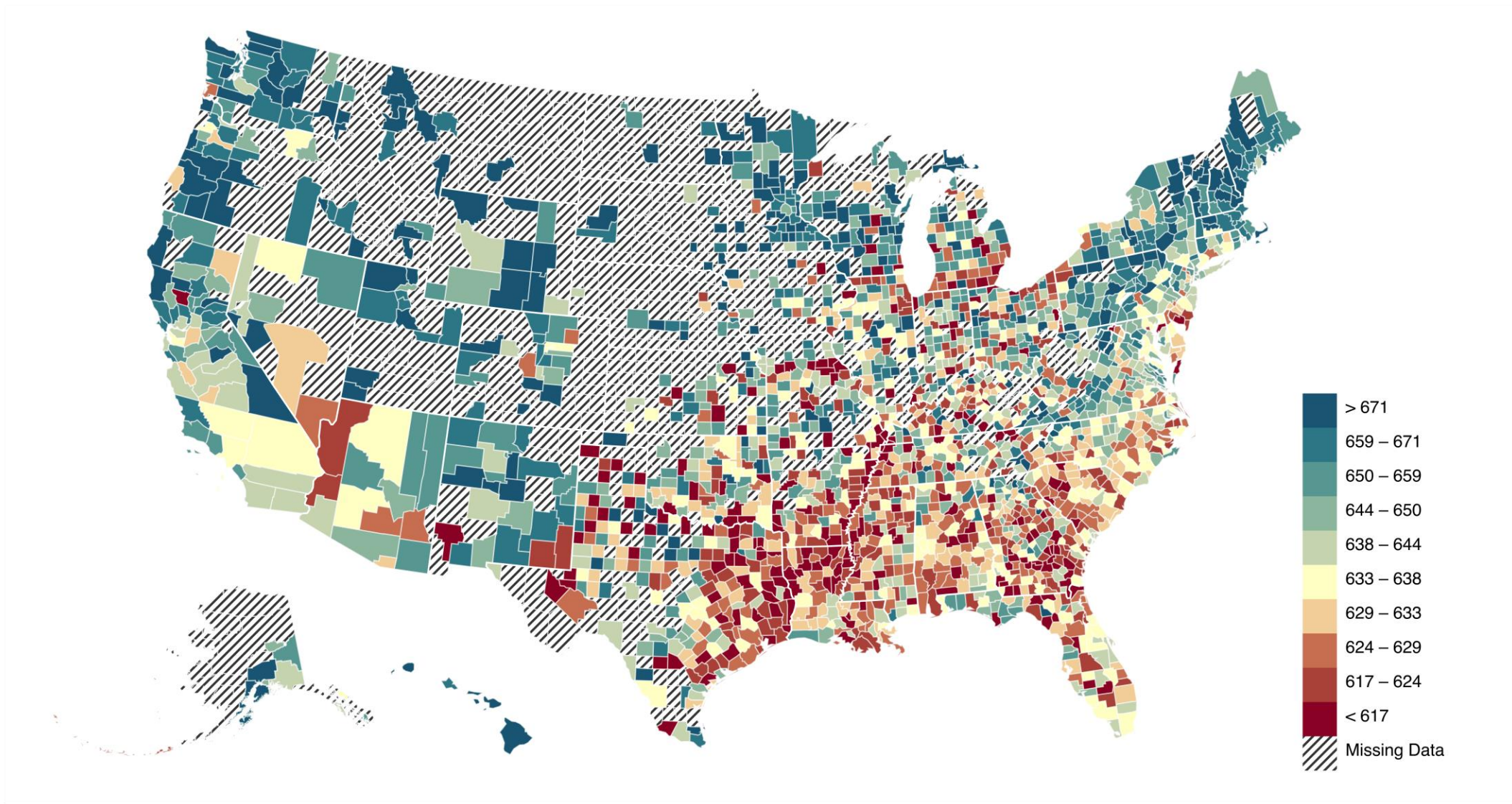
Credit Score Black-White Gap by County



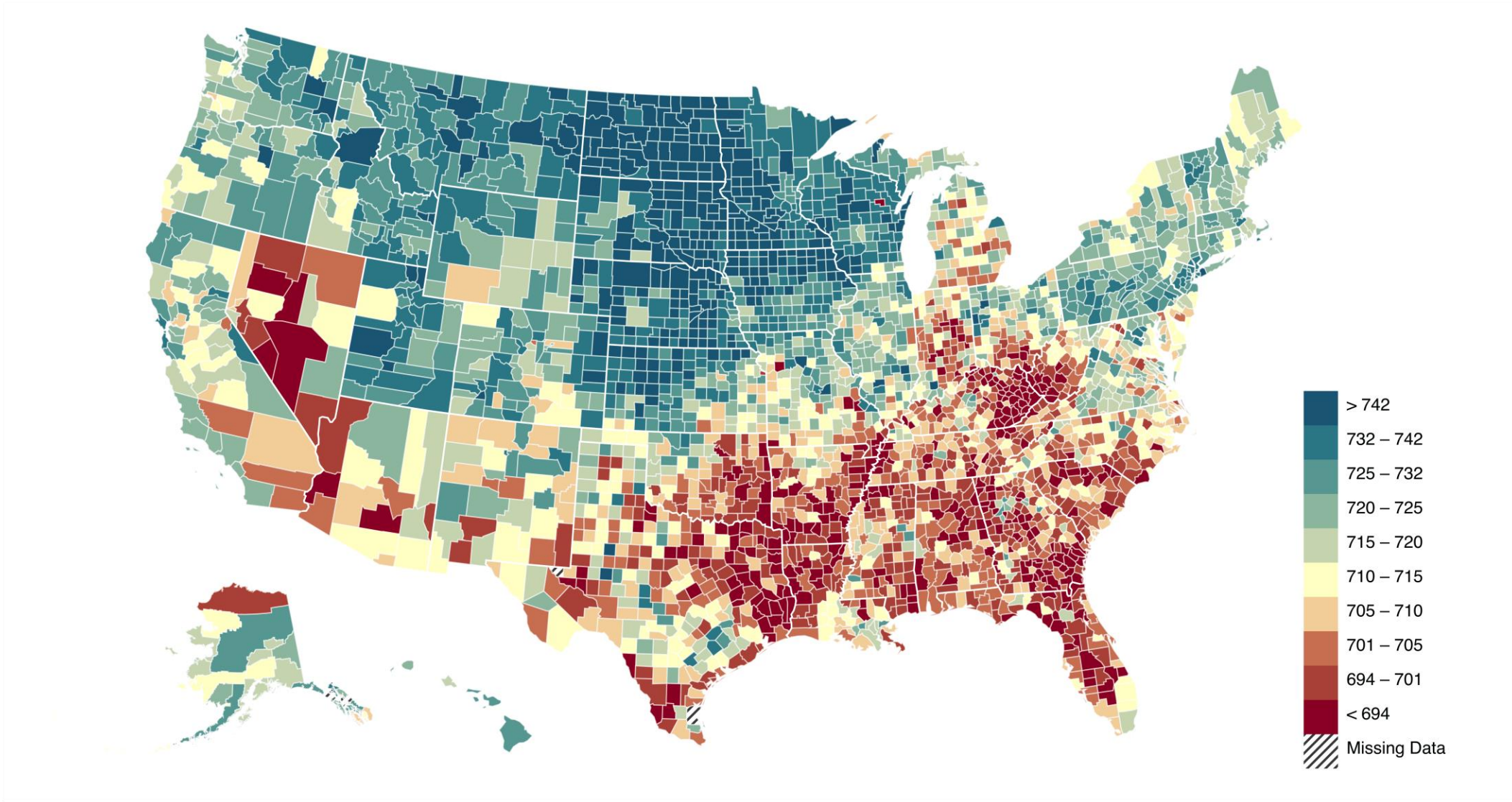
Credit Scores by County for Black Individuals with 25th Pctl Parental Income



Credit Scores by County for Black Individuals with 75th Pctl Parental Income

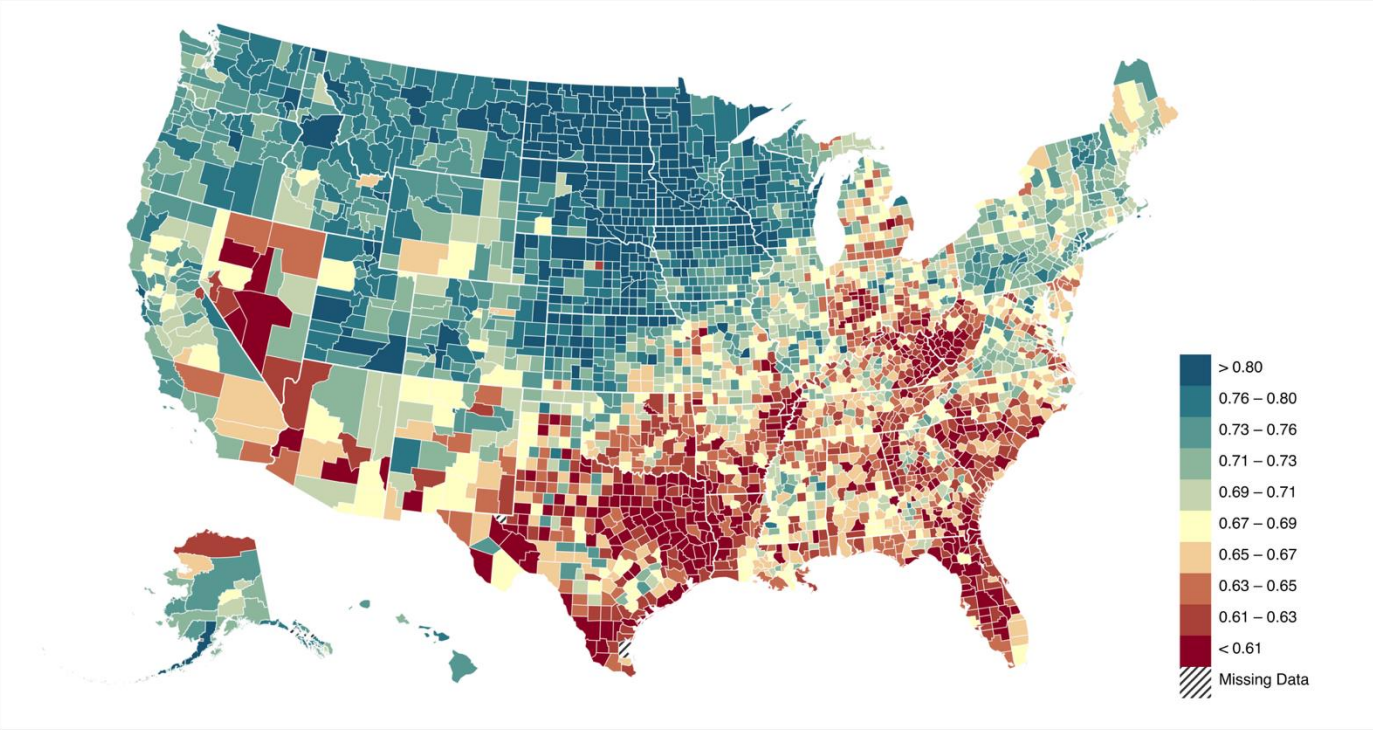


Credit Scores by County for White Individuals with 75th Pctl Parental Income

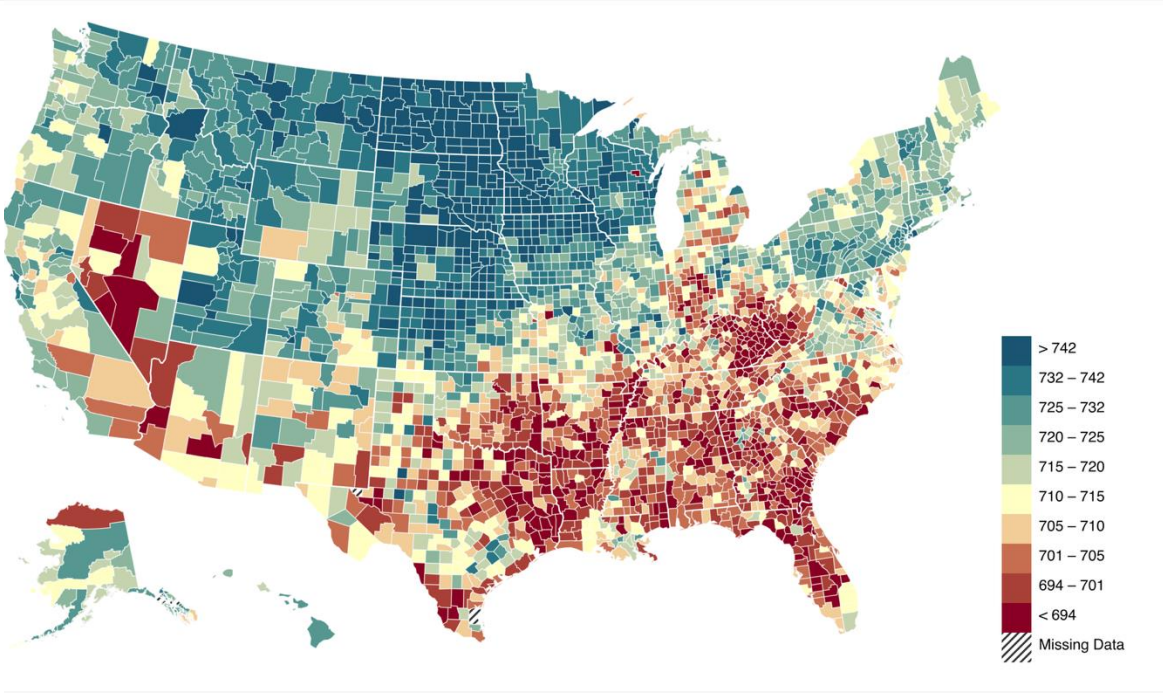


Credit Score and Delinquency, by County

White Individuals with 75th Percentile Parental Income



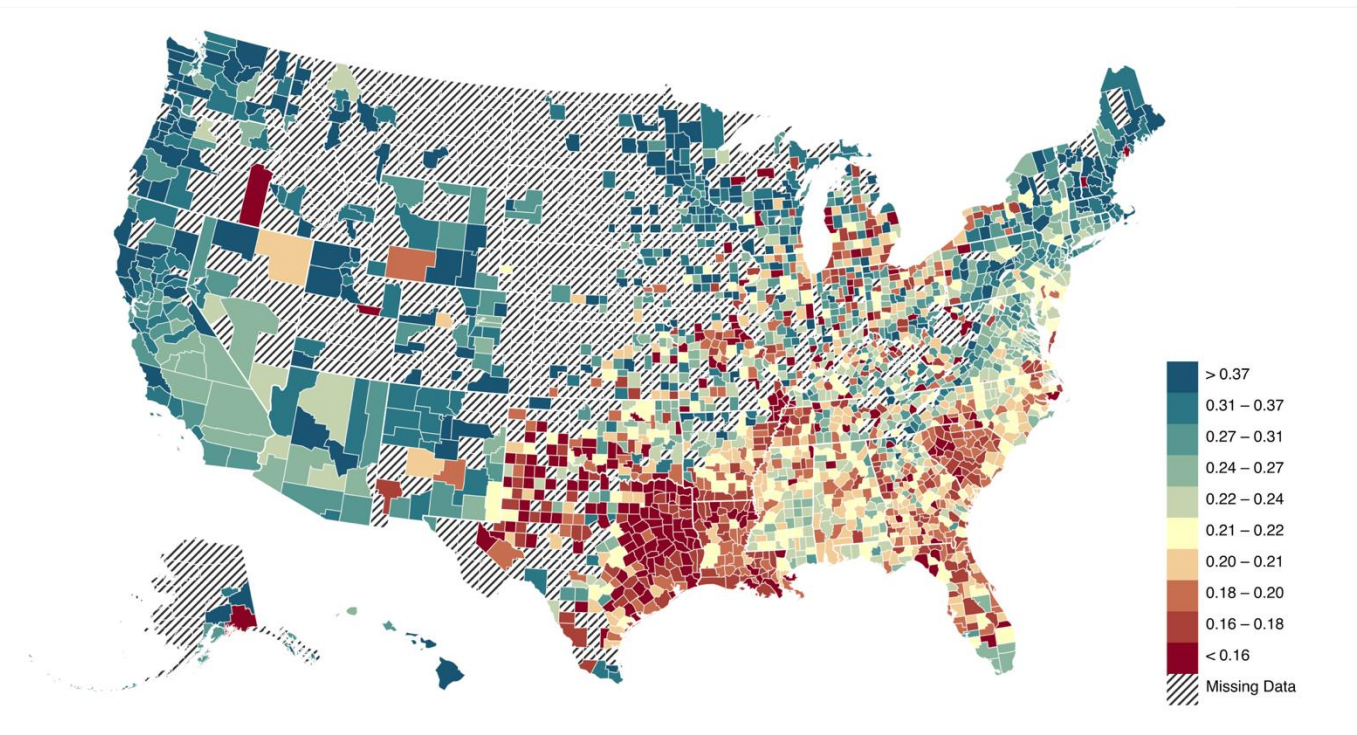
Repayment



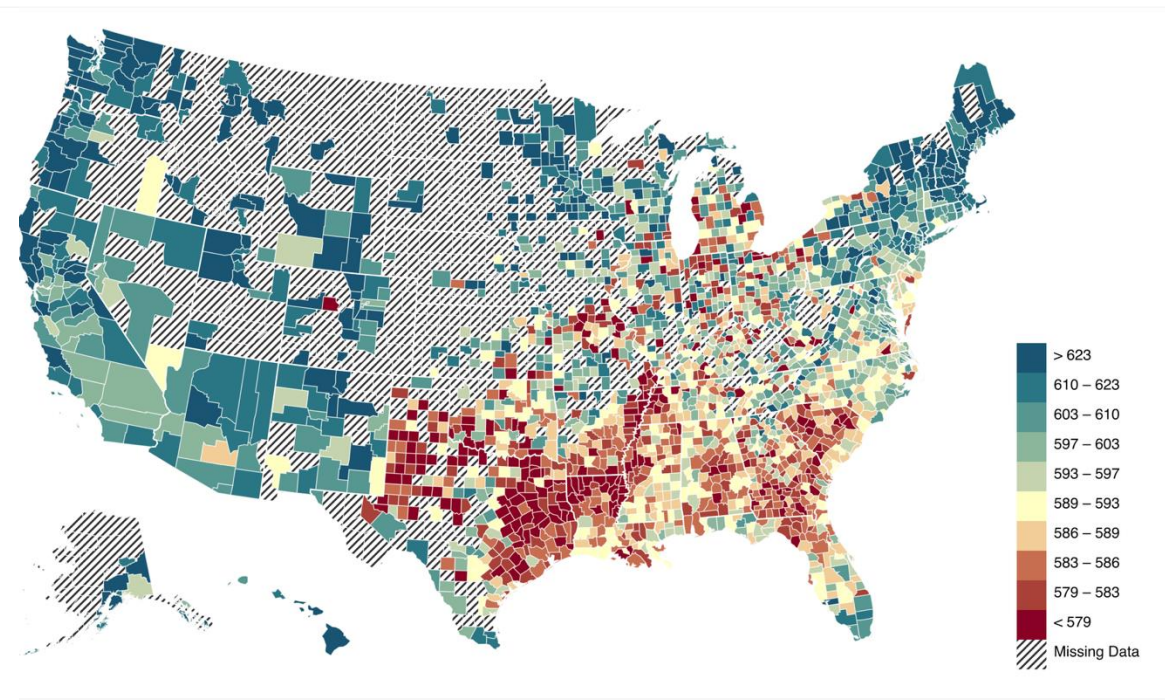
Credit Score

Credit Score and Delinquency, by County

Black Individuals with 25th Percentile Parental Income



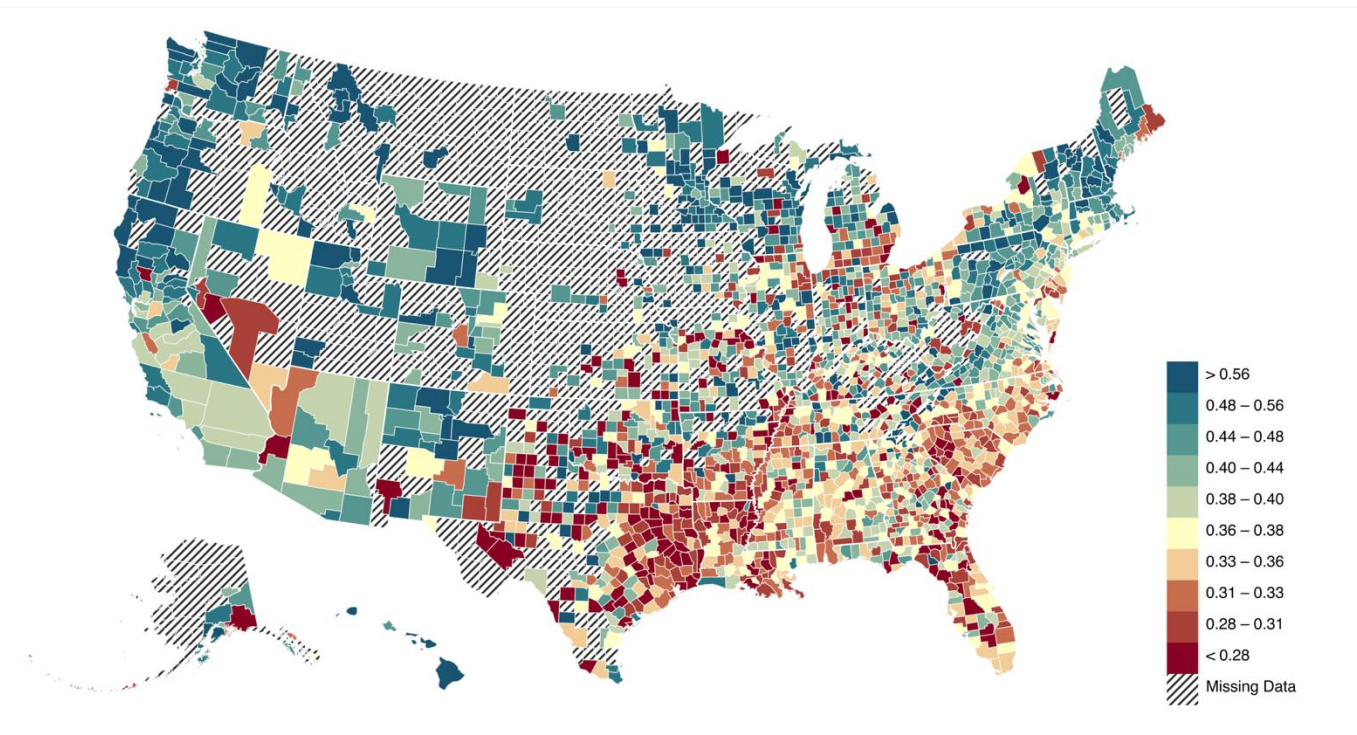
Repayment



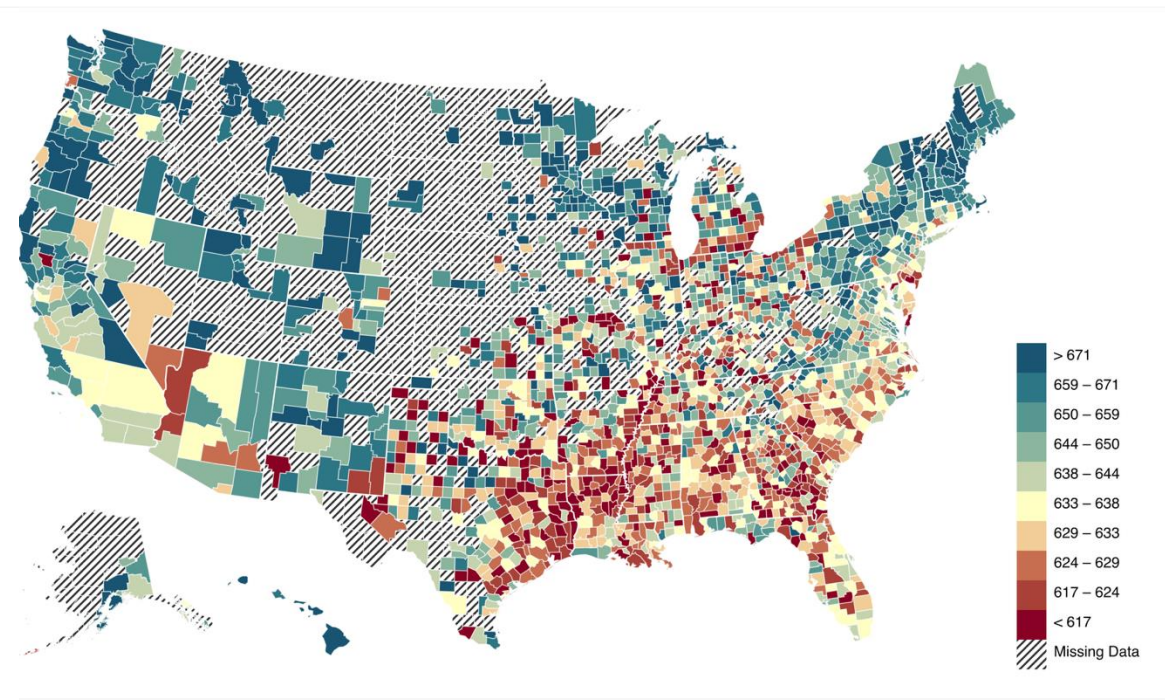
Credit Score

Credit Score and Delinquency, by County

Black Individuals with 75th Percentile Parental Income



Repayment



Credit Score

Takeup of Credit

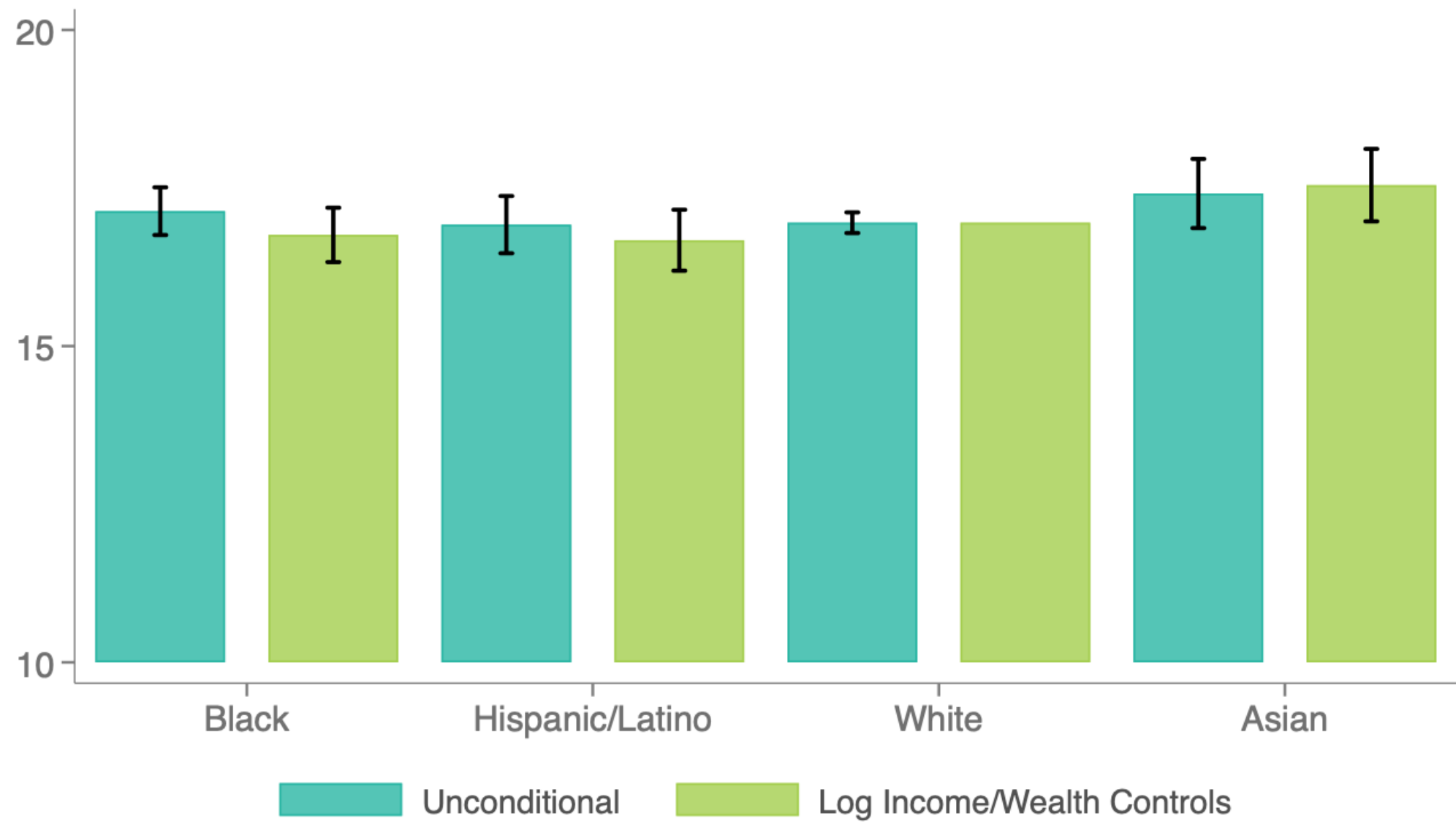


What Drives Differences in Repayment? The Role of Formal Credit Terms

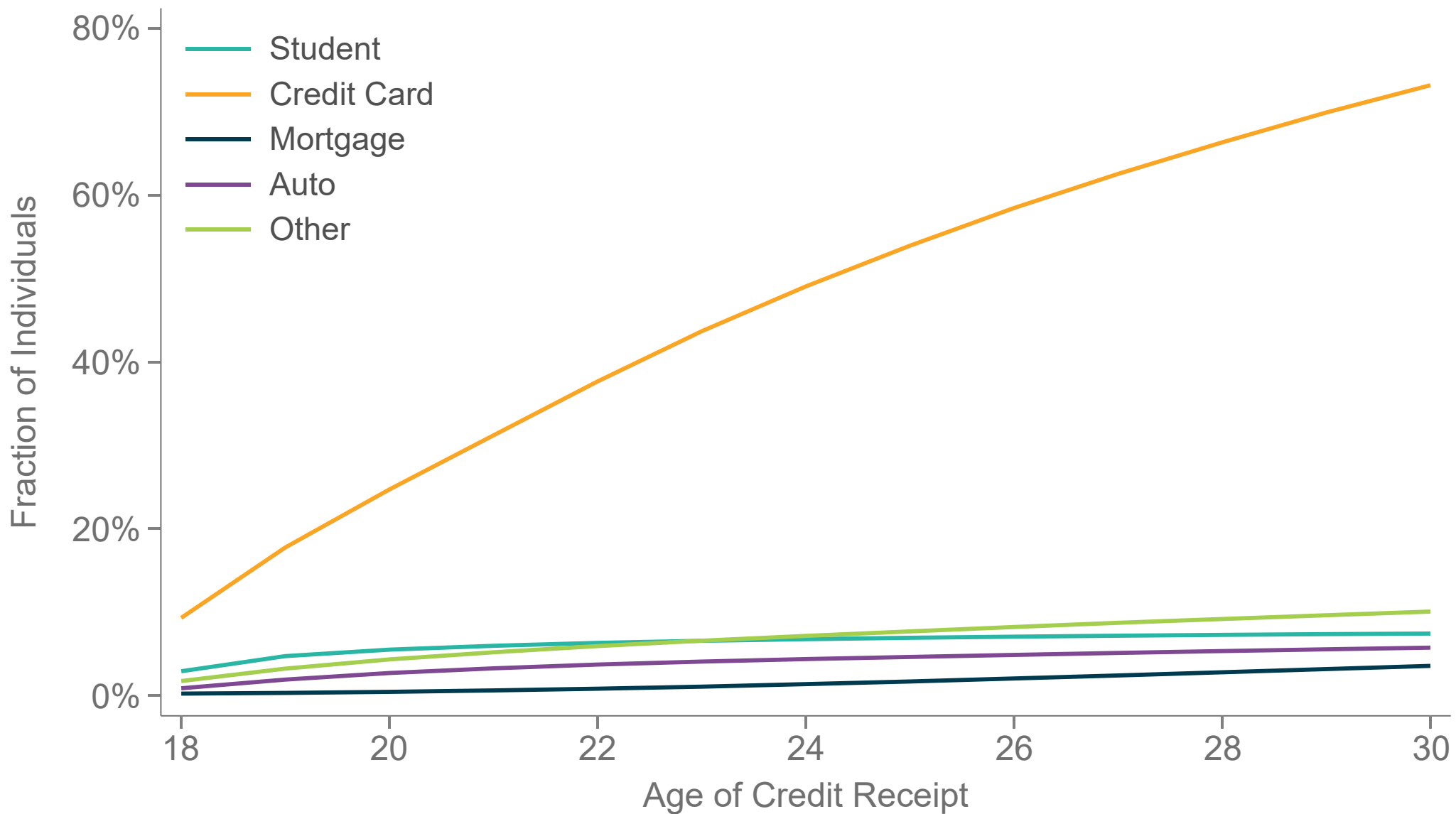
- Existing literature documents Black individuals obtain worse terms in auto lending and mortgage markets, even conditional on creditworthiness (Lanning, 2021; Bartlett et al., 2022; Butler, Mayer, and Weston, 2023; Raymond, 2024)
- Differences in formal sector credit terms could drive repayment if terms have causal effect on repayment
- We don't believe this is a primary driver of the non-repayment patterns:
- Delinquencies emerge early in life primarily for credit cards, student loans, and delinquencies on collections from utilities, phone, TV, and medical bills
 - Standardized terms for student loans
 - Using the SCF, we find similar credit card terms by race for 22-30 year olds



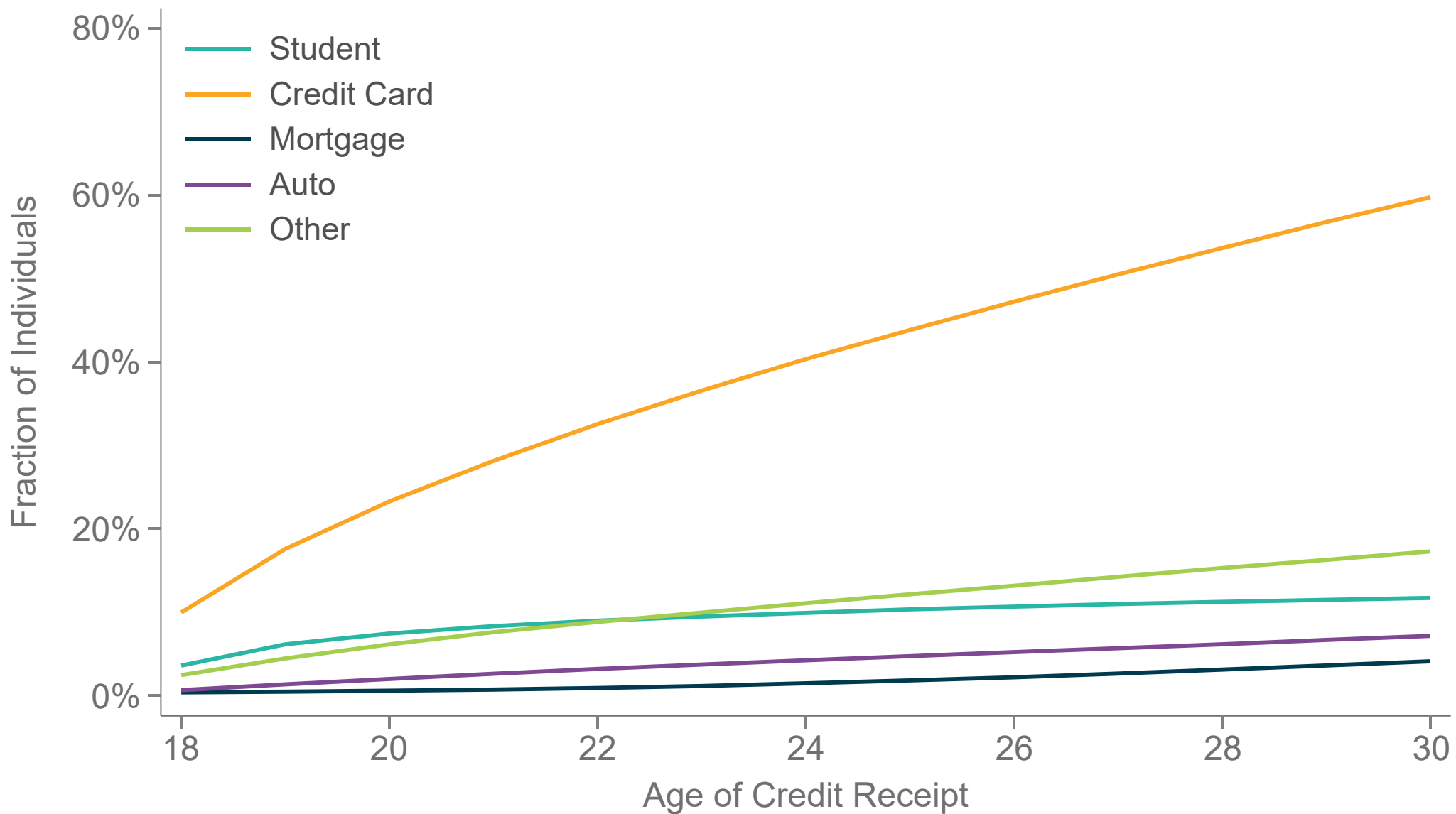
Role of Credit Terms



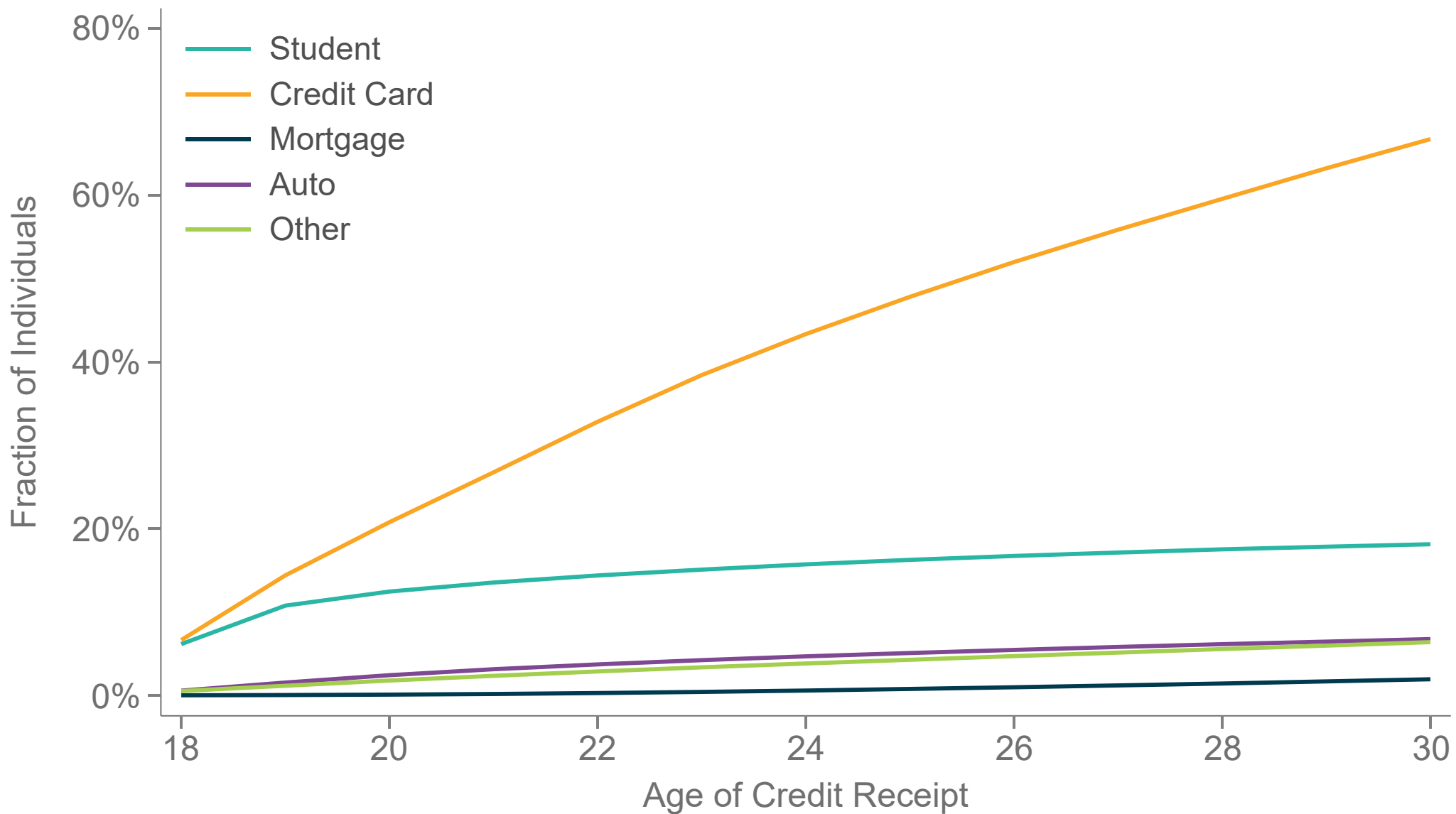
First Tradeline by Age For White Individuals in 2004



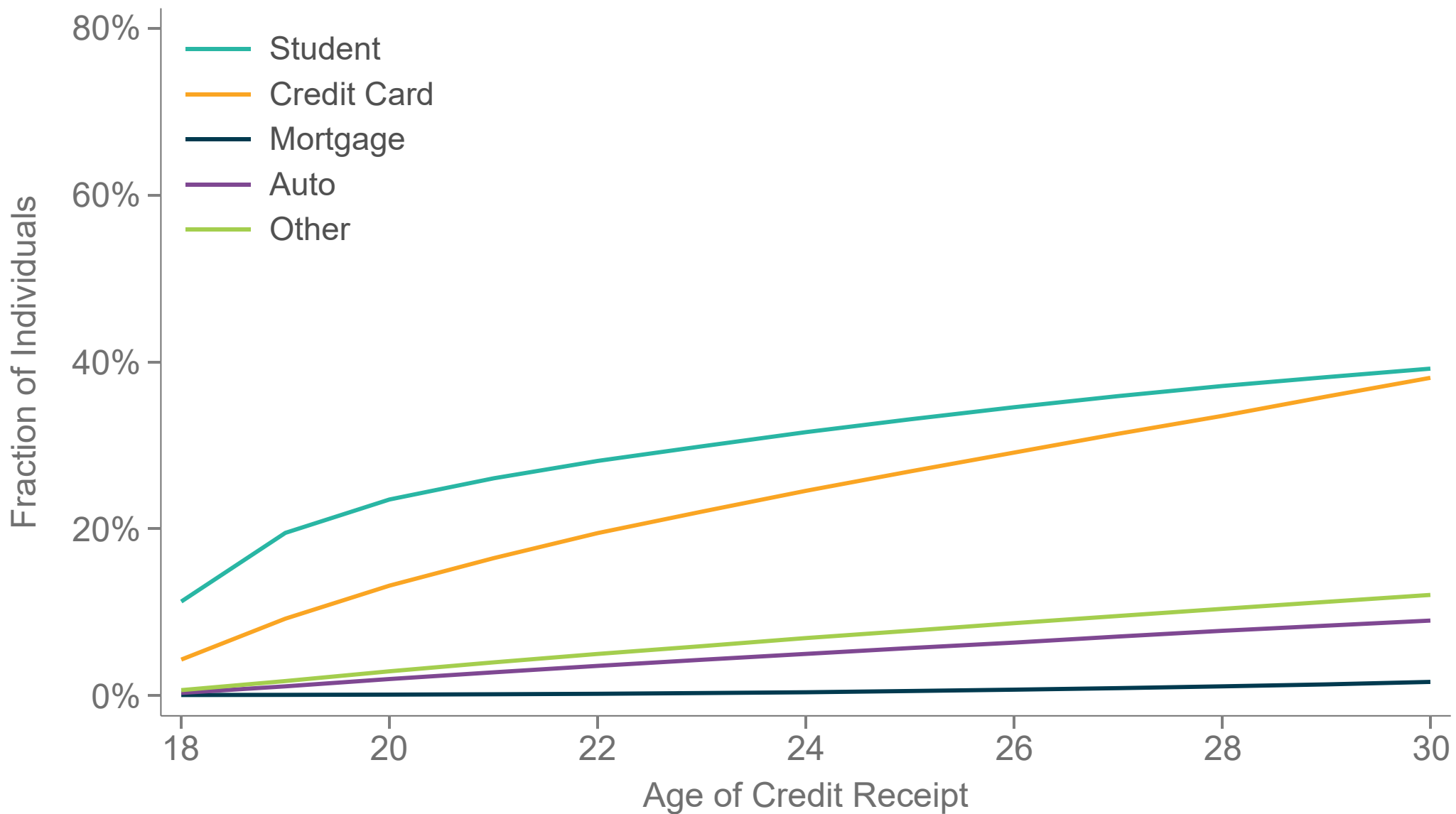
First Tradeline by Age For Black Individuals in 2004



First Tradeline by Age For White Individuals in 2020



First Tradeline by Age For Black Individuals in 2020

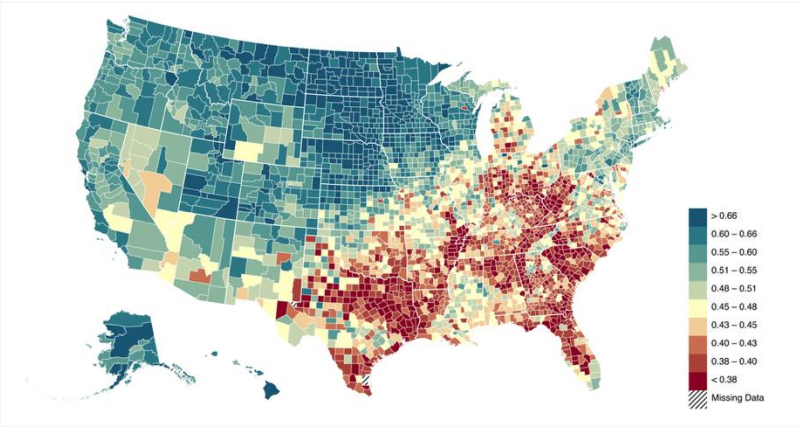


Social Capital

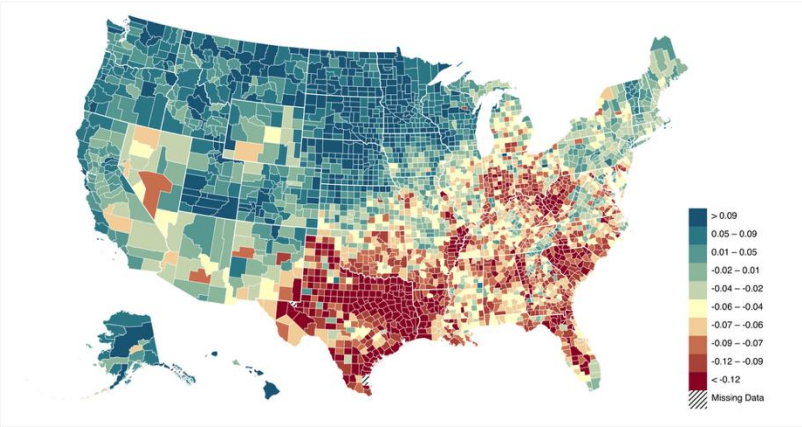


Repayment in 2020 versus Upward Income Mobility

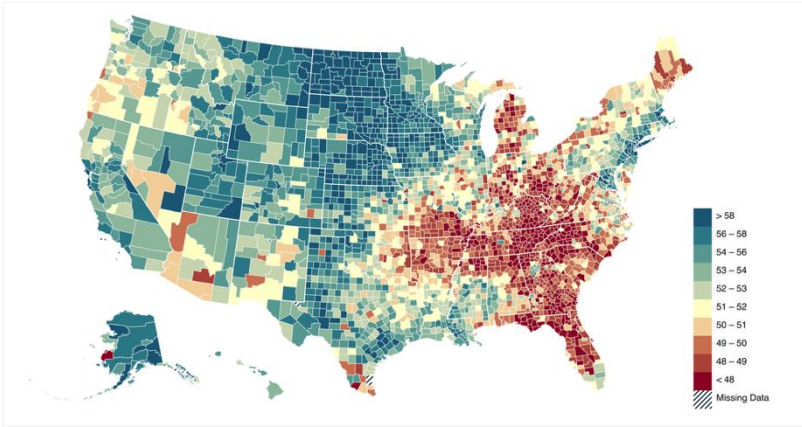
White Individuals with 25th Percentile Parental Income



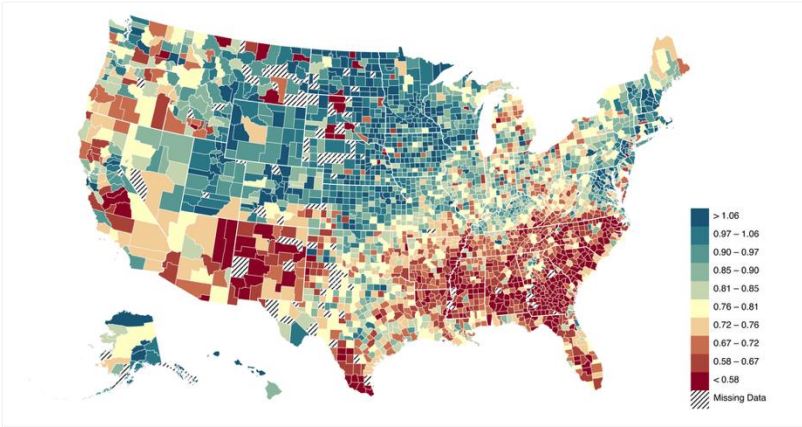
Repayment (Credit Bureau Data)



**Repayment
Conditional on Adult Income**



Upward Income Mobility (Tax Data)



**Economic Connectedness
(Facebook Data)**



Role of Social Capital

- Two potential explanations for why childhood environment and social capital / economic connectedness might affect repayment in adulthood:
- **Financial network:** You know people who can give you money if you need it
- **Learned Behaviors:** You learn from or absorb the behaviors of others
- Conduct survey of ~800 individuals aged 22-30 on Prolific to measure:
 - Self-reported delinquency
 - Race/class/hometown
 - Measures of lending to/from one's network and ability to obtain resources from friends/family
 - Similar bilateral patterns in representative surveys (CES, PSID, SCF, NCFS, BPS)



Role of Informal Networks in Repayment (Prolific Survey)

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

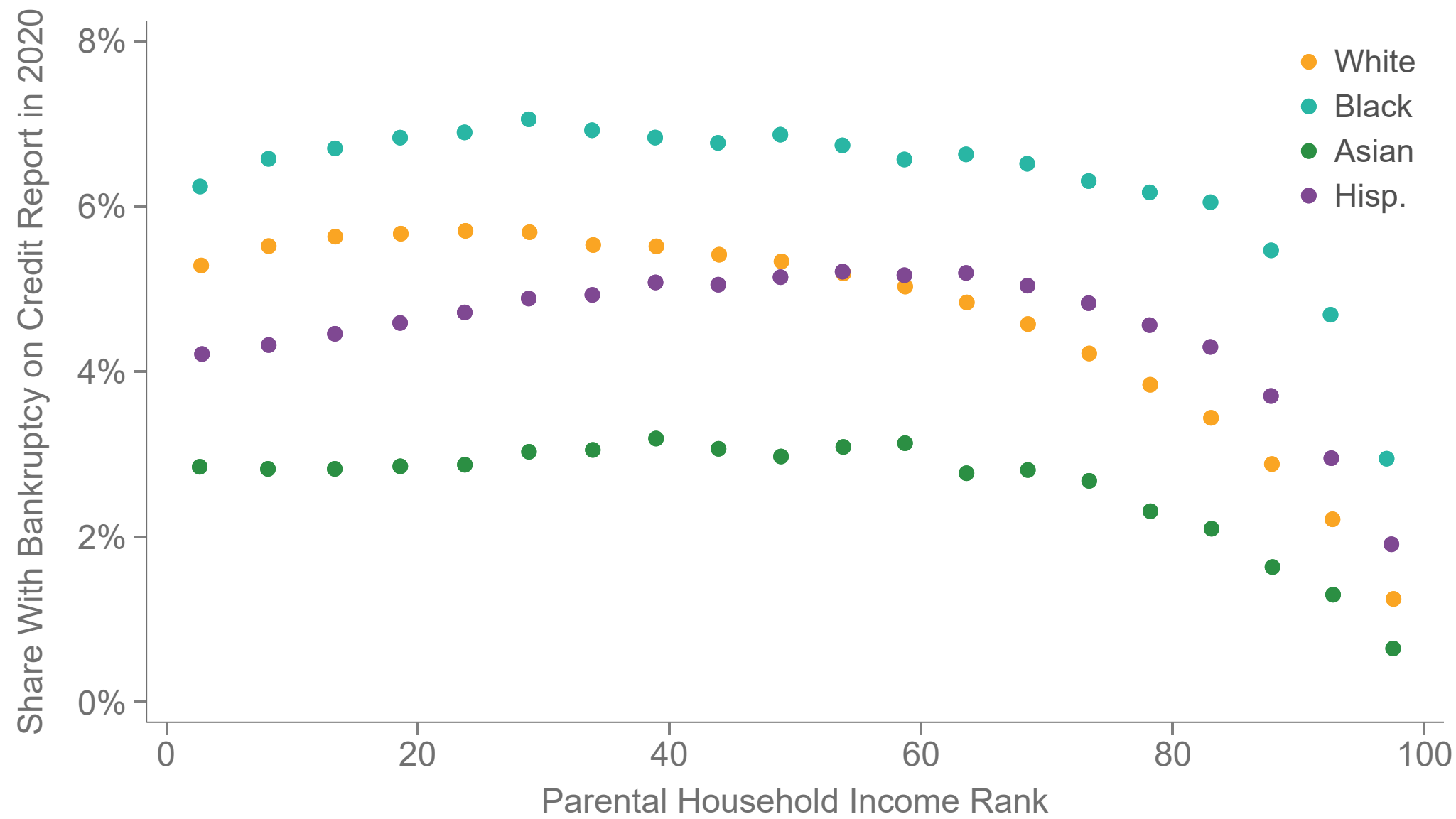
Financial Literacy and Non Repayment (SCF)

	(1)	(2)	(3)	(4)	(5)
Financial Literacy: Inflation	−0.108*** (0.029)	−0.087*** (0.029)	−0.078*** (0.028)		−0.081*** (0.028)
Financial Literacy: Diversification	−0.039 (0.029)	−0.030 (0.028)	−0.017 (0.029)		−0.021 (0.027)
Financial Literacy: Interest	0.015 (0.029)	0.026 (0.028)	0.017 (0.028)		0.014 (0.028)
Log HH Income		−0.085*** (0.015)	−0.053*** (0.018)	−0.082*** (0.014)	−0.071*** (0.015)
Log Net Wealth			−0.037*** (0.010)		
Black				0.185*** (0.034)	0.177*** (0.034)
Hispanic				0.035 (0.034)	0.033 (0.034)
Asian				0.178 (0.196)	0.212 (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

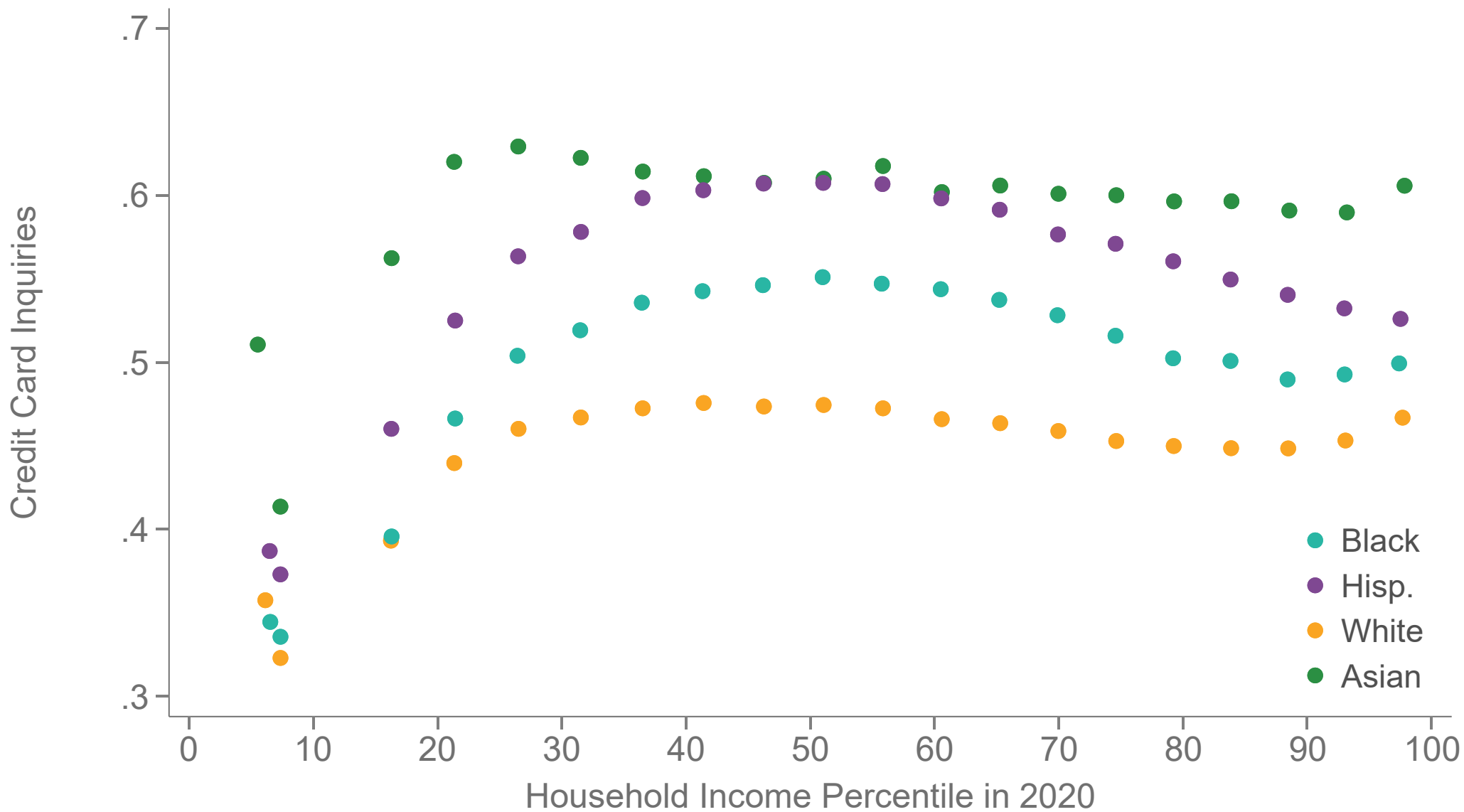
Alternative Credit Use by Race, Class, and Geography (Prolific Survey)

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

Bankruptcy by Parent Income and Race

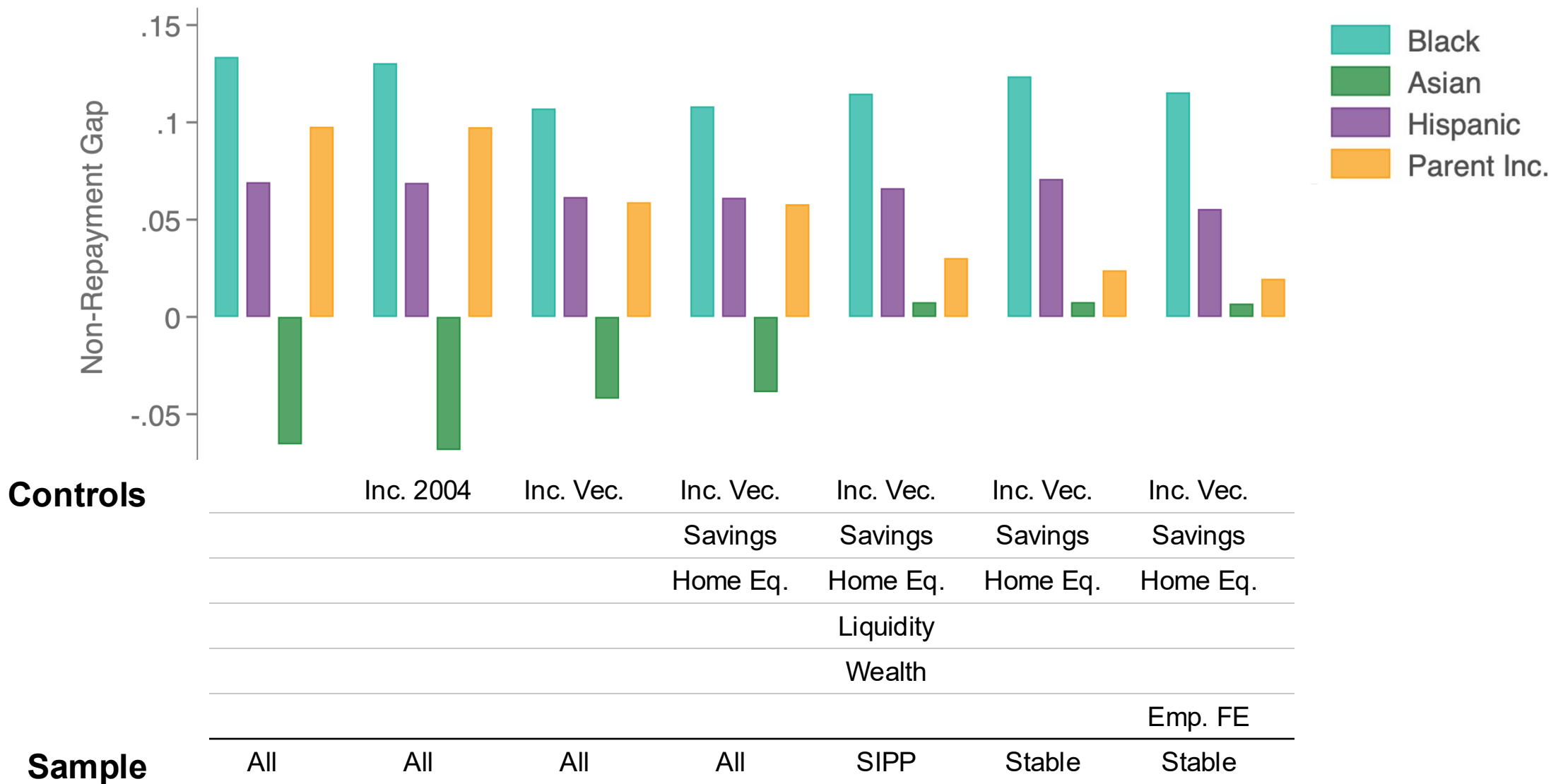


Number of Credit Card Inquiries

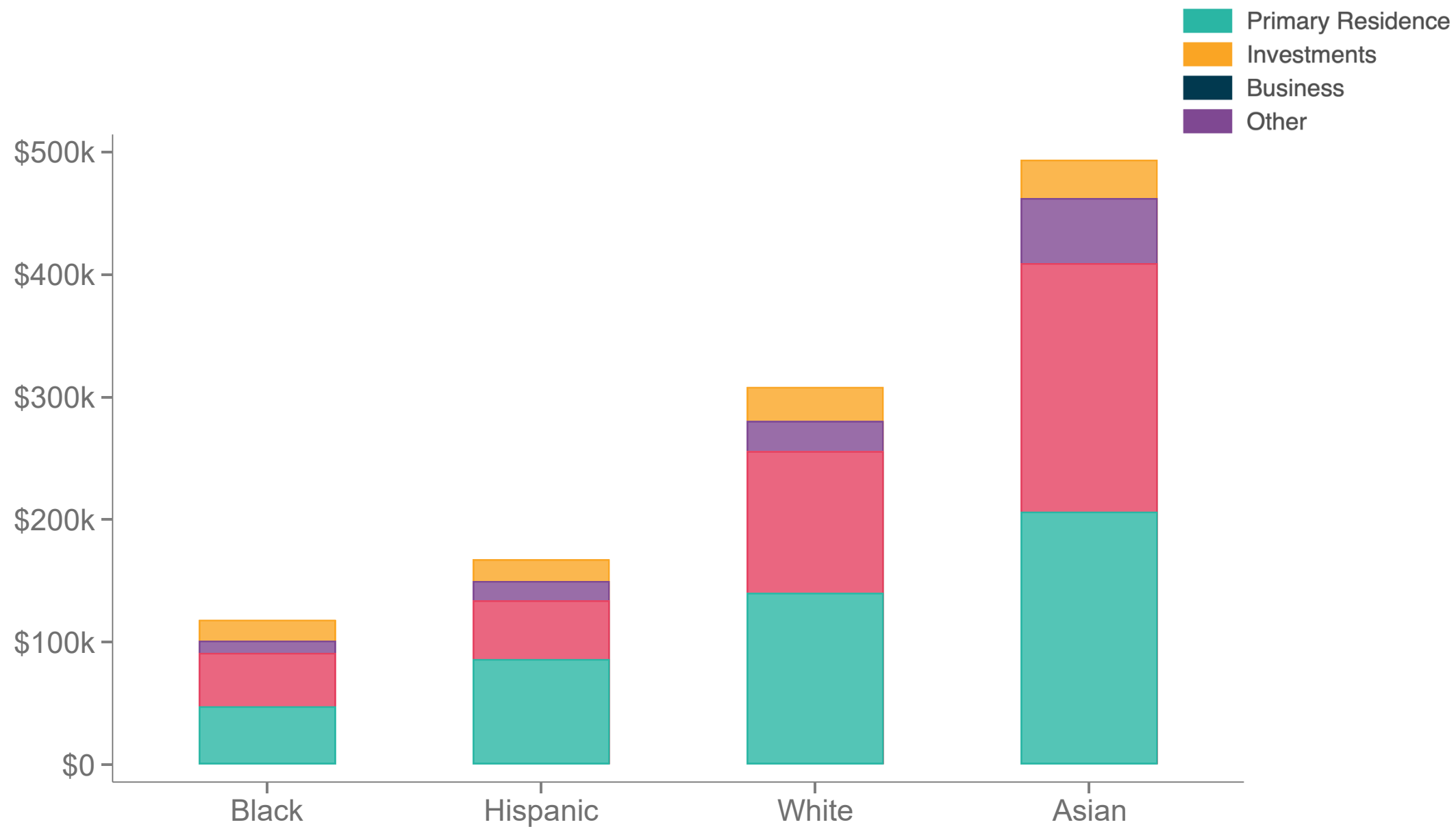


The Role of Income and Wealth in Explaining 90+ Day Delinquency in 2008

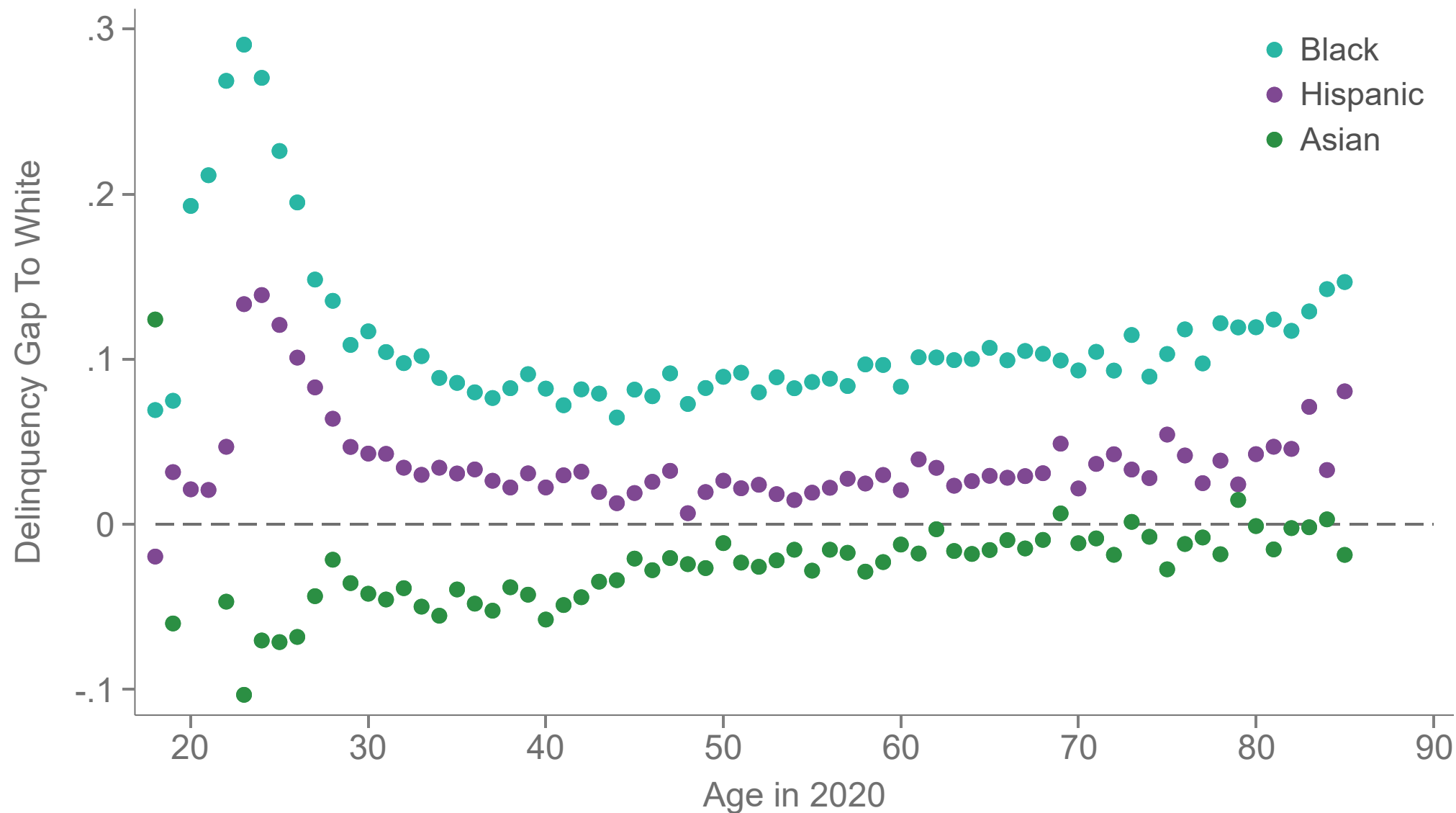
Controlling for Credit Score



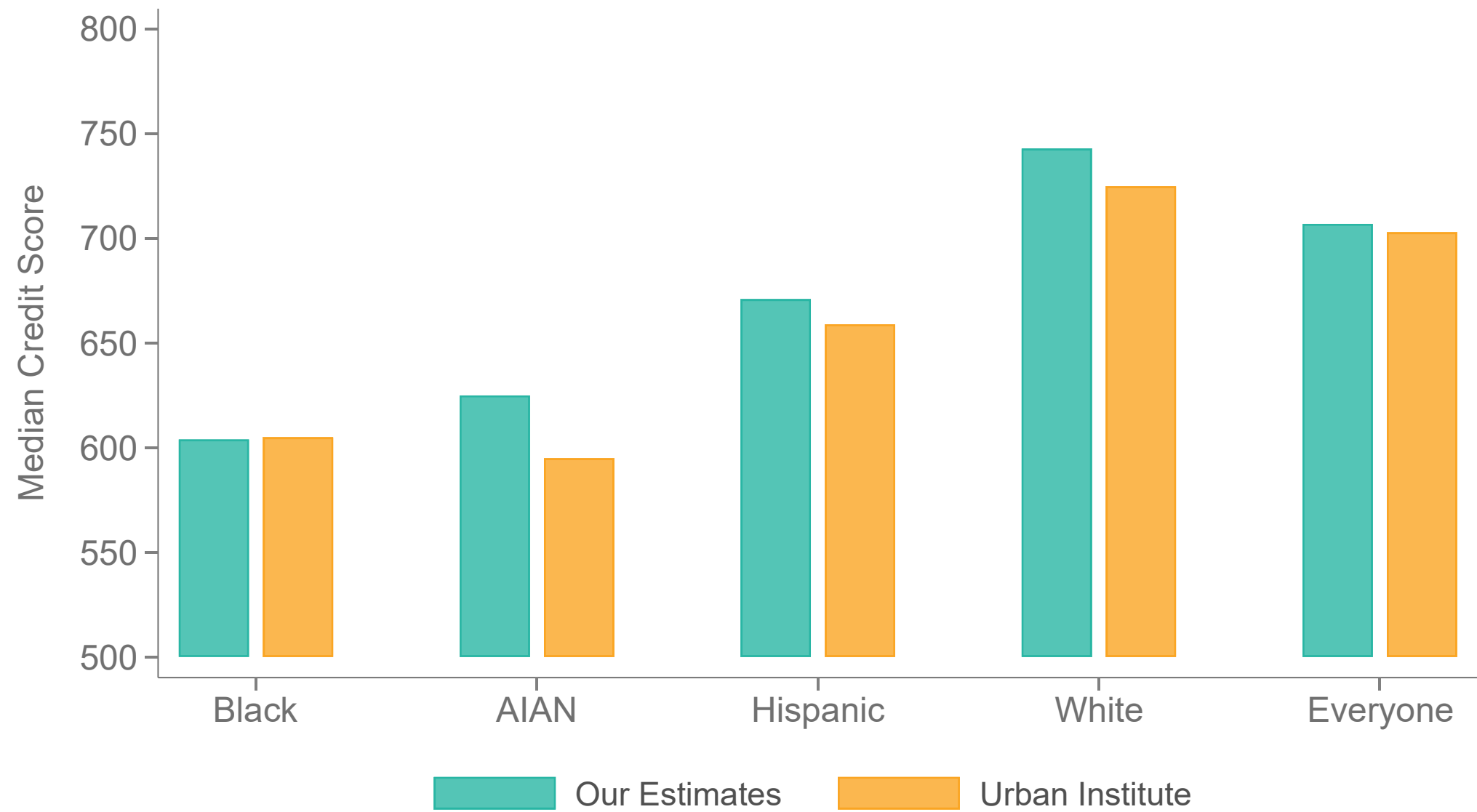
Composition of Total Assets by Race (SIPP)



Race Dummies on Delinquency Relative to White by Age



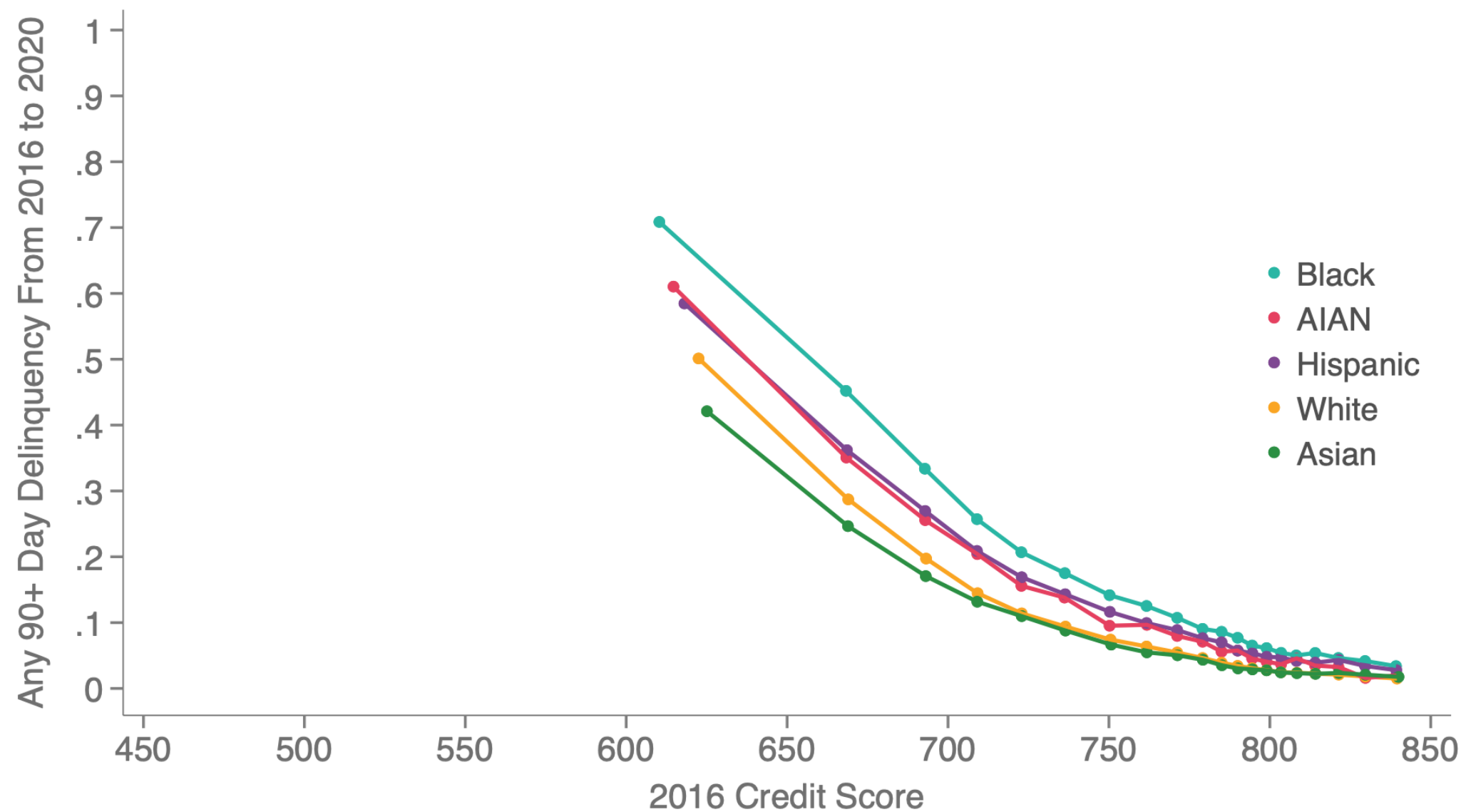
Comparison of Our Estimates to Urban Institute



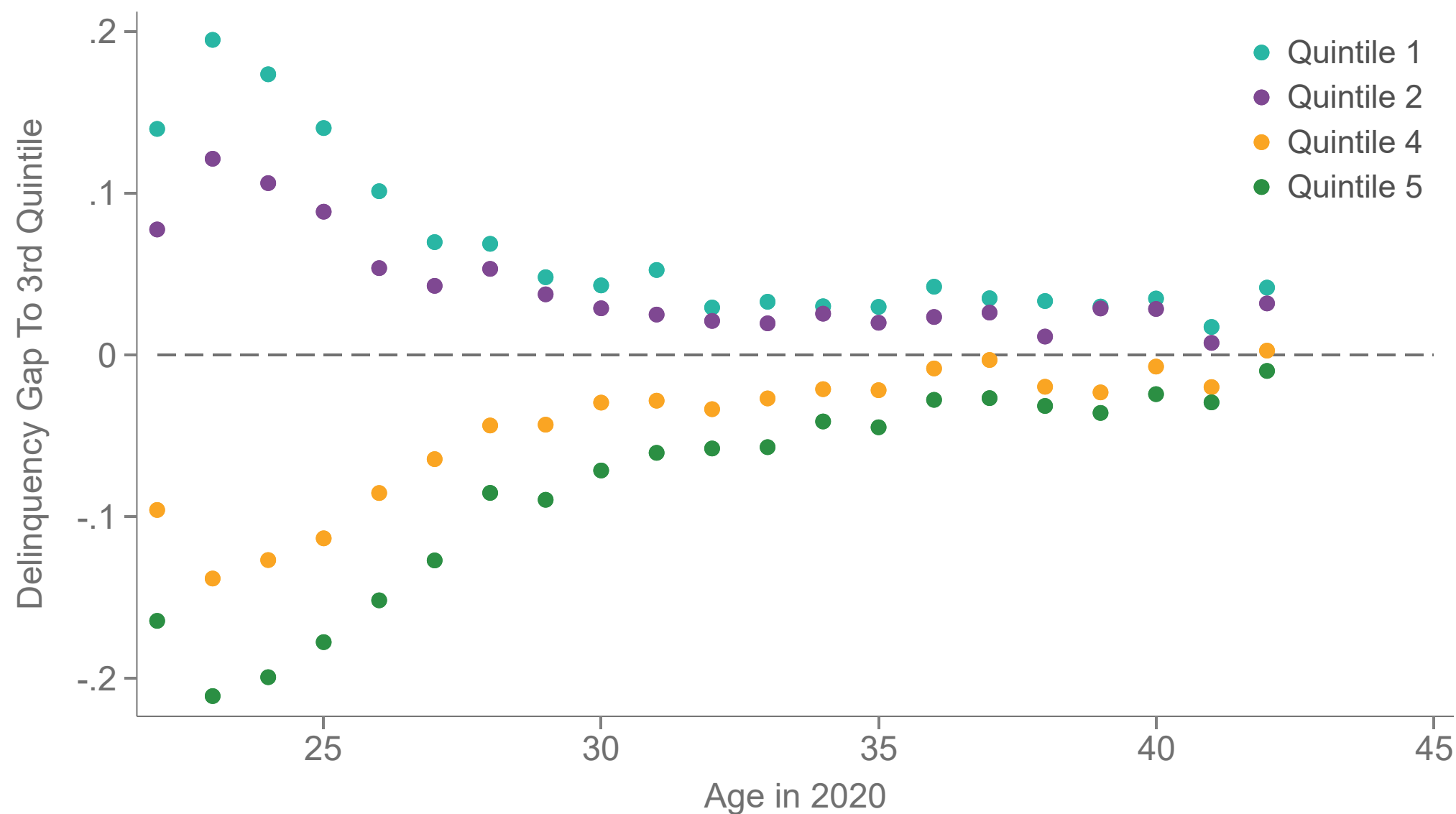
Calibration Bias Among Perfect Borrowers



Credit Scores are Predictive of Future Delinquencies Of Previously Perfect Borrowers by Race



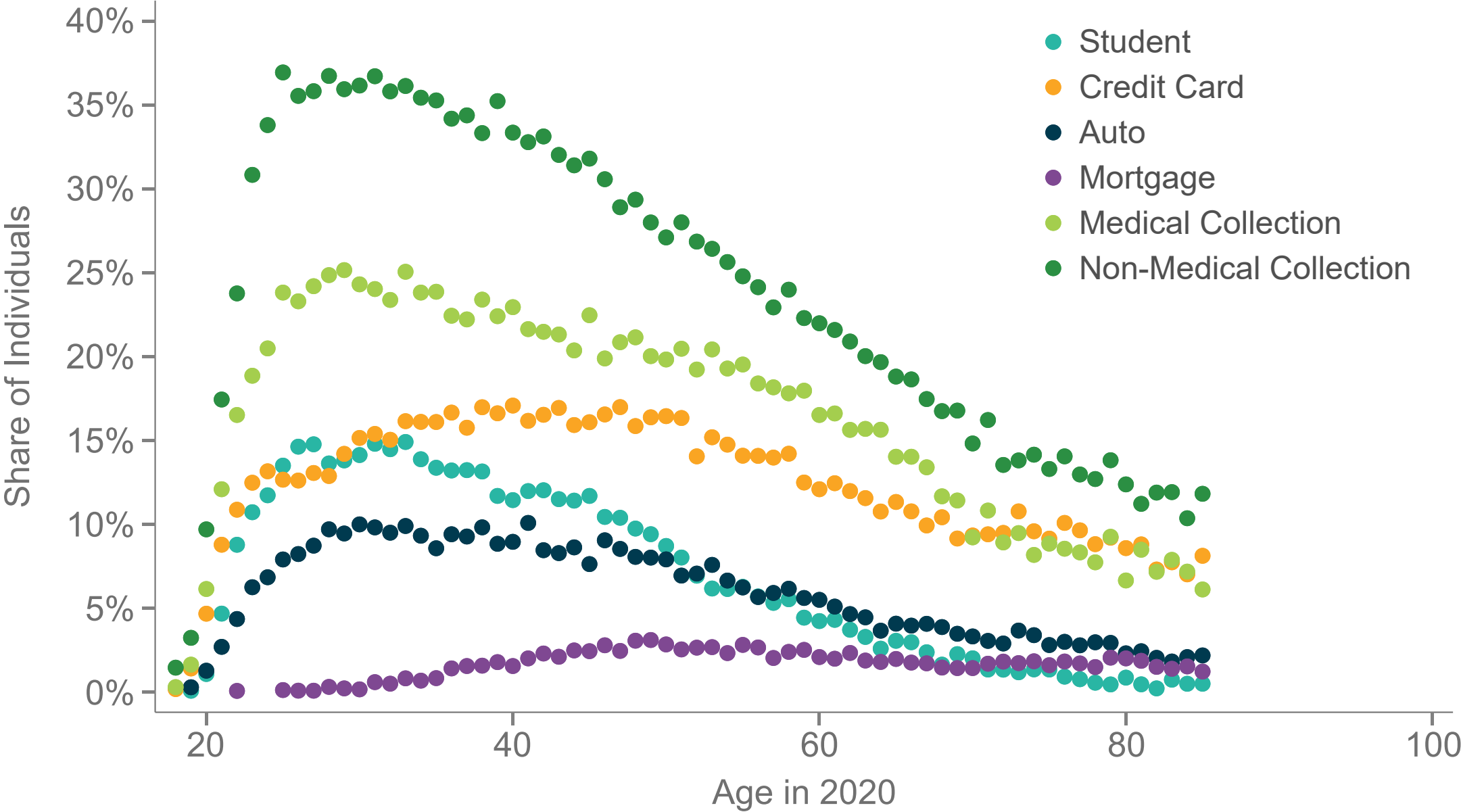
Class Dummies on Delinquency Relative to Bottom Quintile by Age



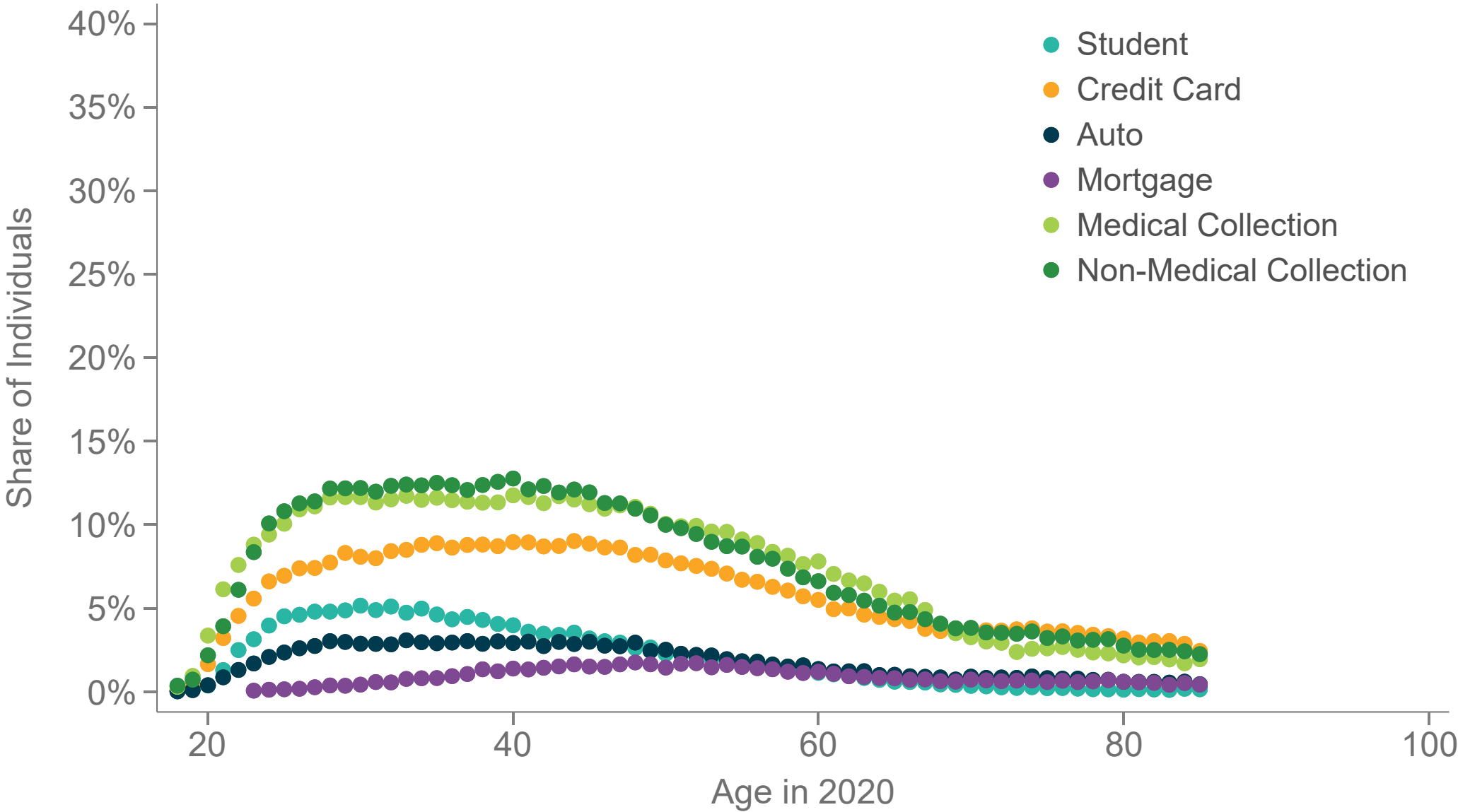
Lifecycle of Late Payments By Tradeline



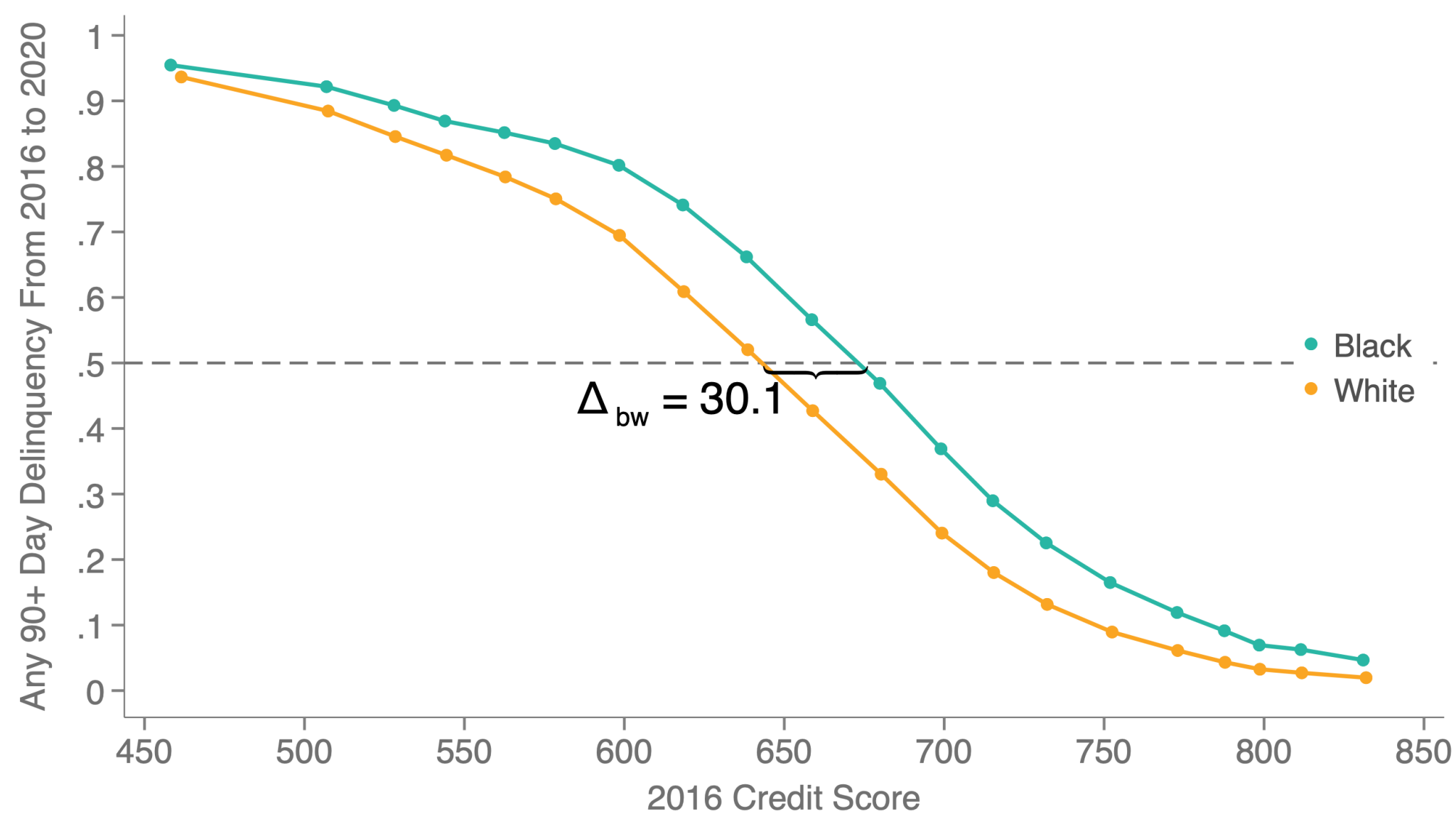
90+ Day Late Payment Breakdown



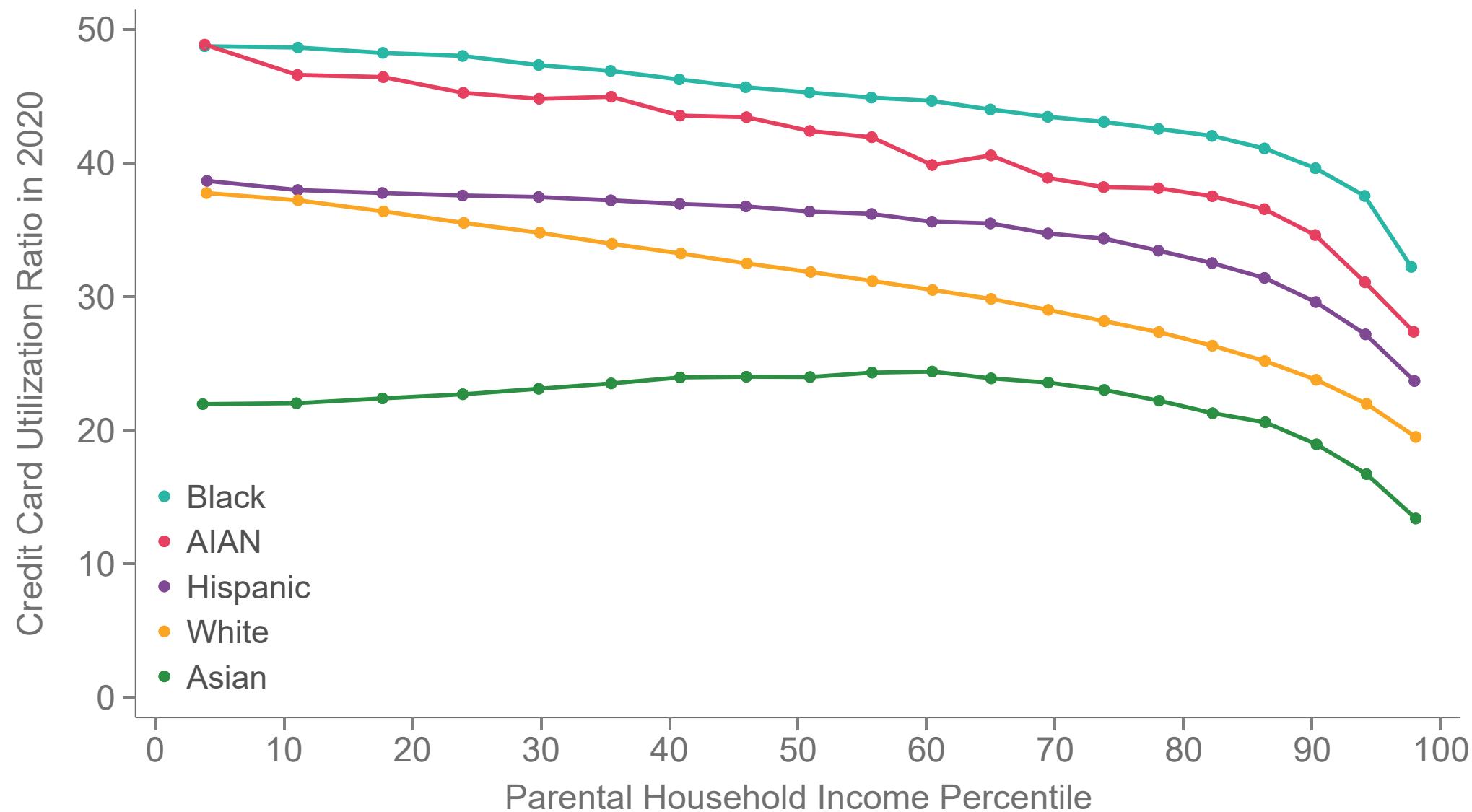
90+ Day Late Payment Breakdown



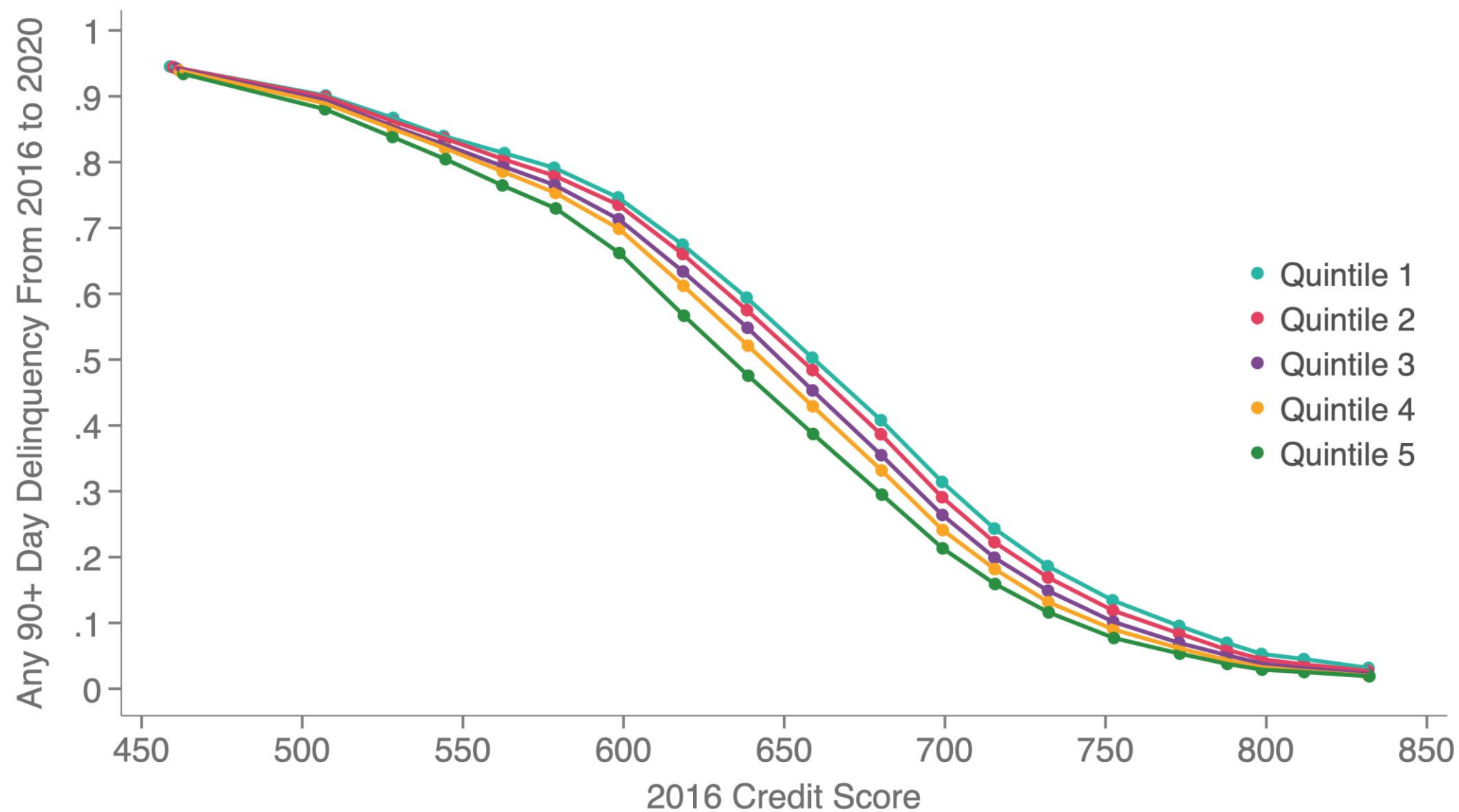
Calibration: Credit Scores are Predictive of Future Delinquency



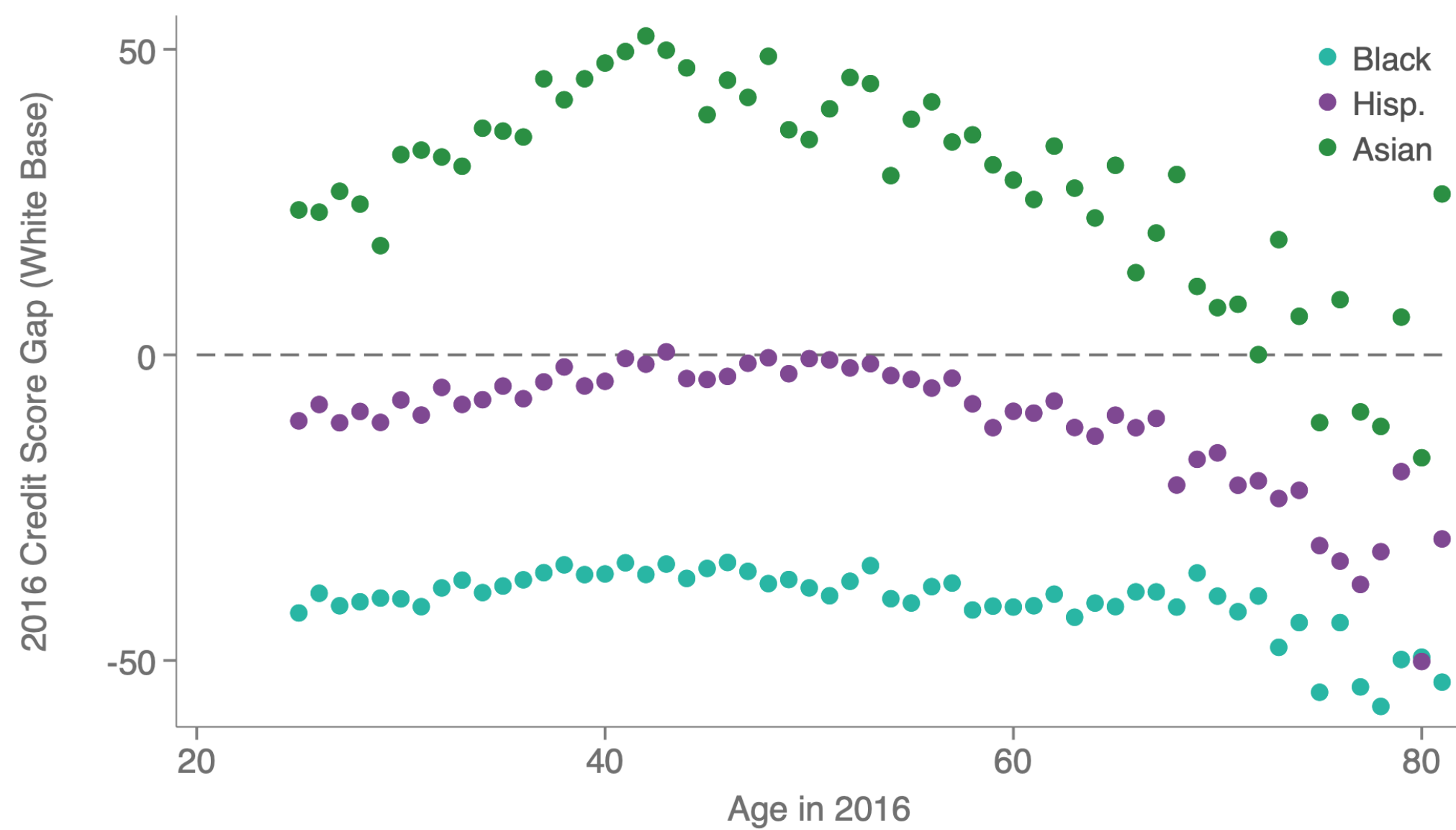
Credit Card Utilization by Race and Parent Income 2020



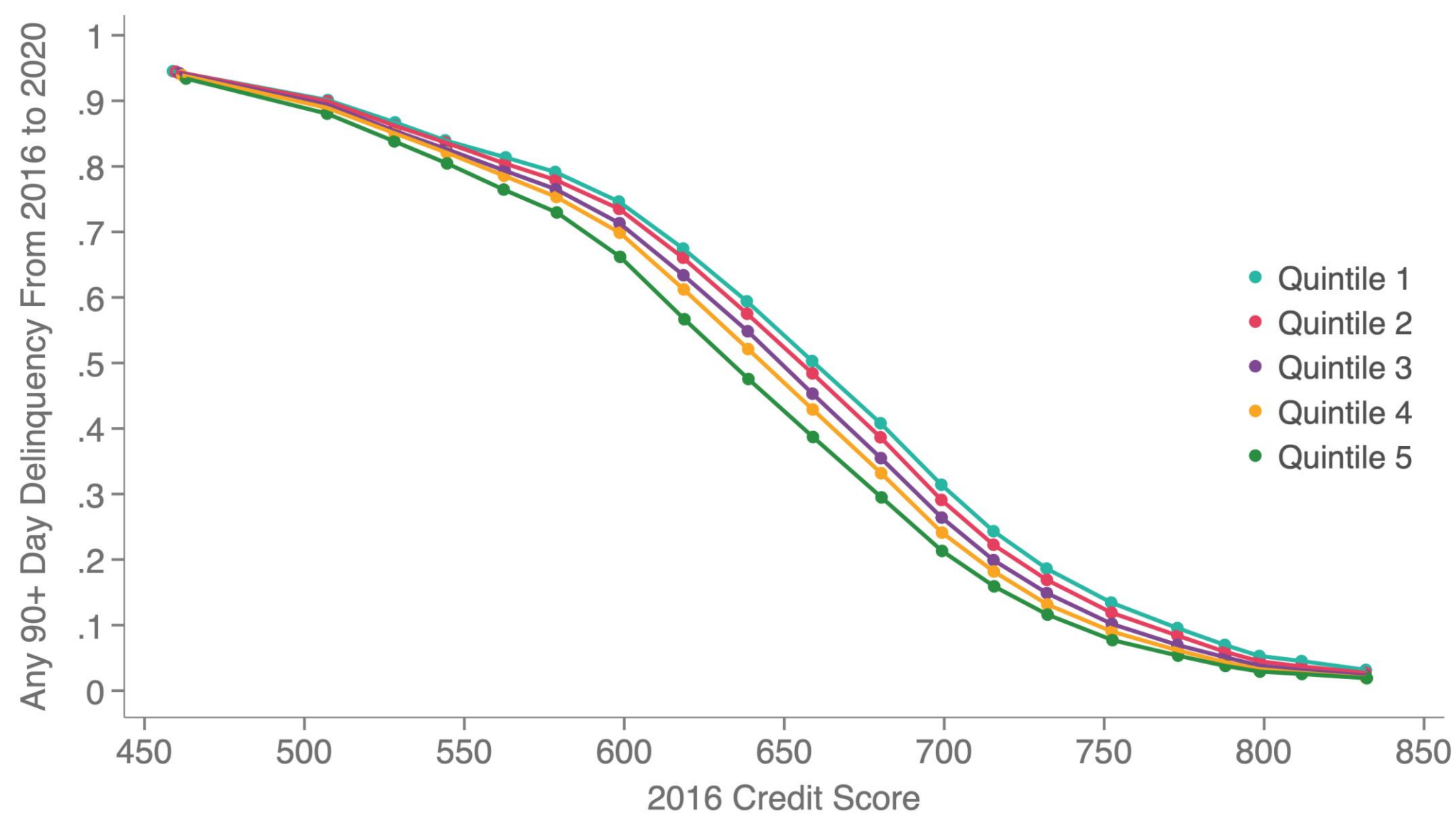
Calibration of Credit Score by Age



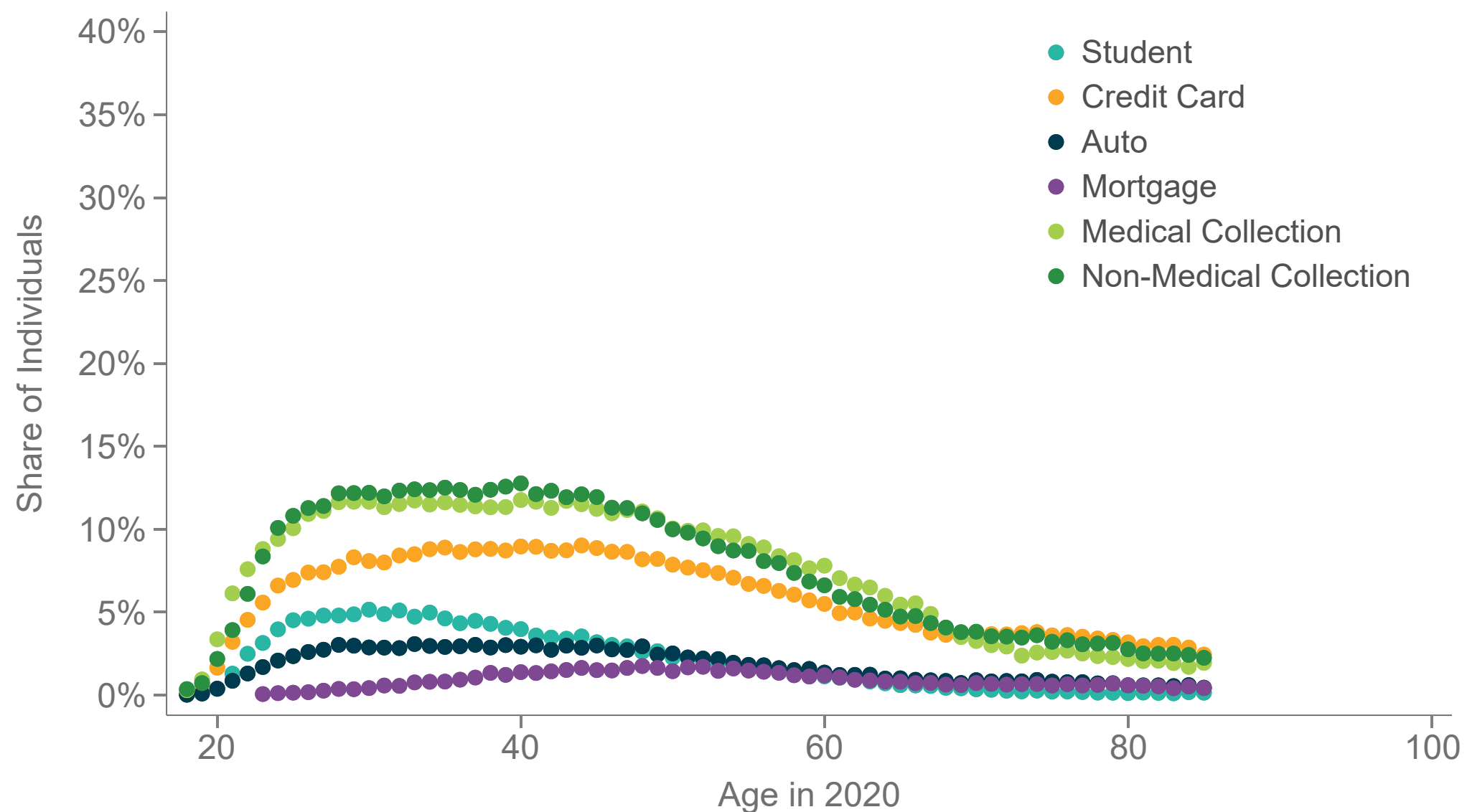
Balance of Credit Score by Age



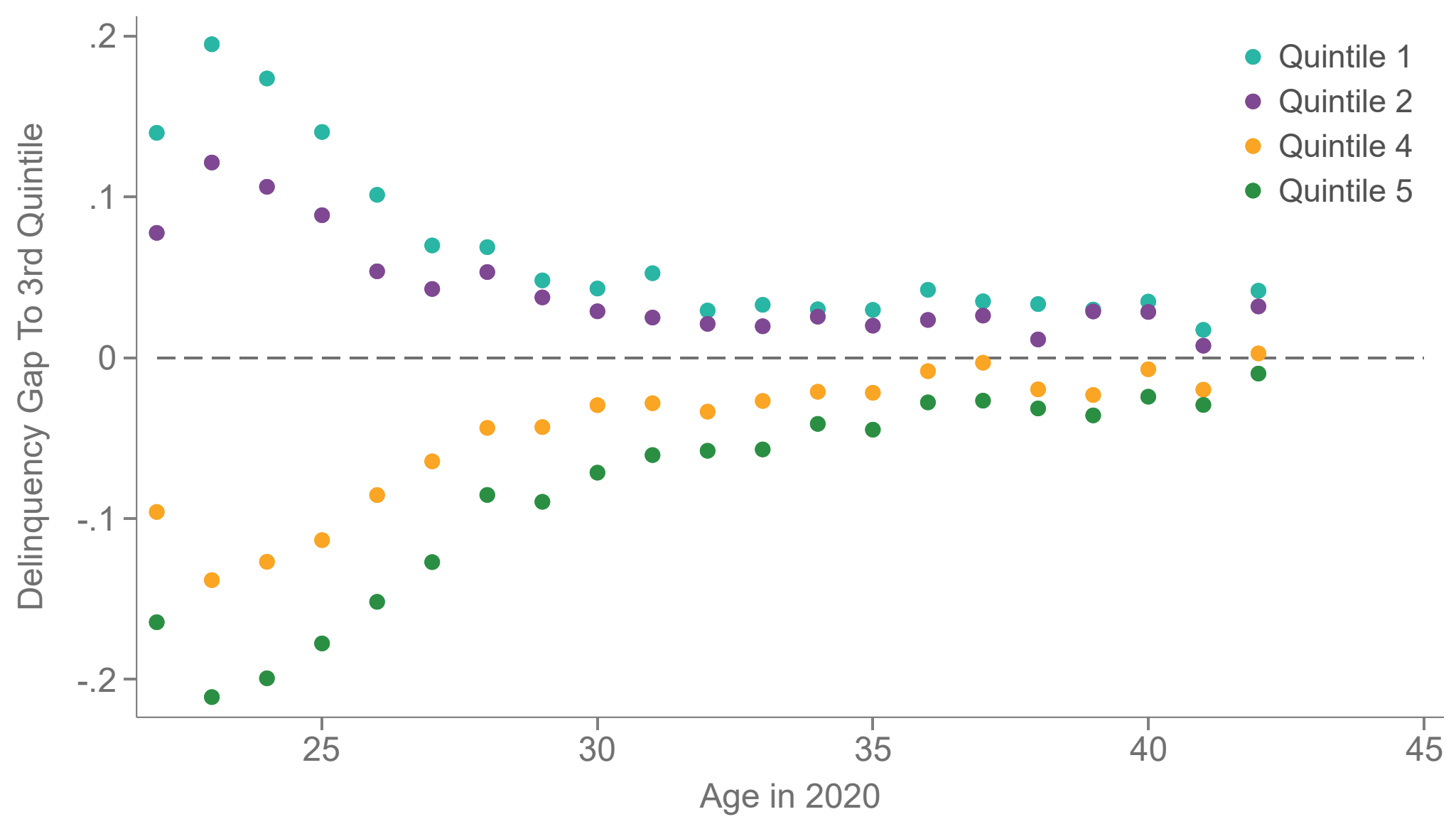
Calibration Bias by Parental Income



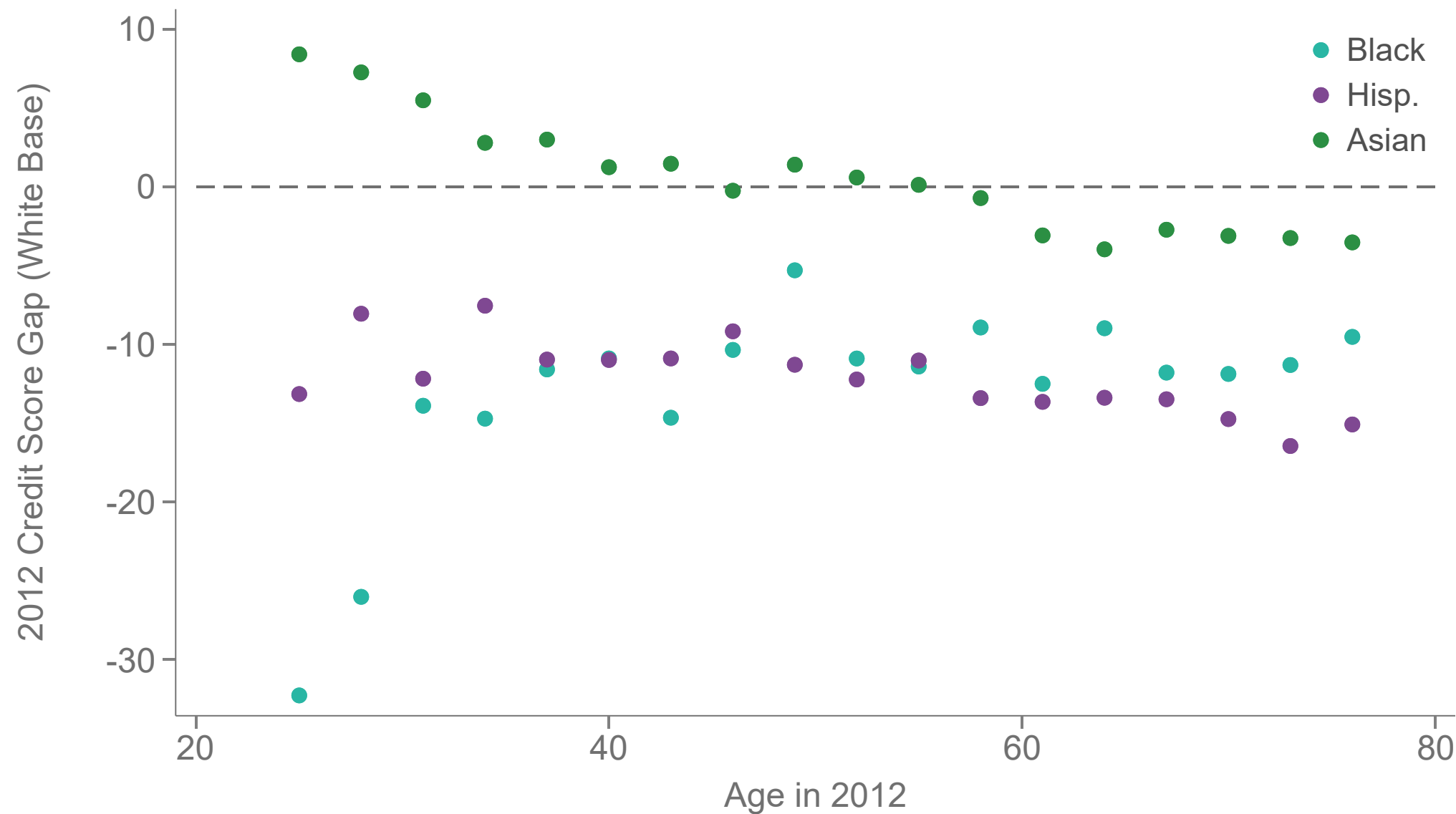
Delinquencies and Collections By Age (White)



Parental Income Calibration of Credit Score by Age



Balance of Credit Score by Age: “Perfect 23-Year Repayment Sample”



Bankruptcy by Race

