Racial Disparities In Young Adults' Credit and Debt and the Effectiveness of State Initiatives to Protect Young Adults During the COVID-19 Pandemic

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Study Goals and Research Design

Policy Motivation

01

During recessions, young adults face long term impacts on their employment & earnings

02

There are large and persistent disparities in credit health along lines of race and ethnicity

03

Racial disparities are at risk of widening after economic shocks

04

Policies have the potential to help people cope with shocks

Research Questions

How did young adults' (ages 20-29) credit health change over the pandemic? Did community-level racial disparities in credit health across communities widen or narrow?

To what extent do community-level factors associated with credit health and differences in wealth-building opportunities explain community-level racial disparities in young adults' credit scores?

How did young adults (ages 20-23, 24-26, and 27-29) in 2020 fare relative to young adults in non-recessionary times (2016) over a three-year period, as measured by credit scores?

To what extent have state policies protected the financial well-being of young adults (ages 20-29) living in communities of color during the pandemic and ameliorated or exacerbated pre-COVID-19 inequities?

Data Sources

Outcome Data

- Credit records from 5 million consumers linked with data on use of alternative financial services loans (e.g., payday loans)
- Includes details on consumers' zip code, age, and use of credit and debt.

Community Data

- ZCTA-level data on share of residents who identify as Black, Hispanic, Native American, or White from the American Community Survey
- County-level data on residential racial diversity and housing wealth from Urban Institute's Mobility Metrics
- ZCTA-level data on income, employment, education, and homeownership from the American Community Survey

Policy Data

- State-level utility shutoff moratoria from the National Consumer Law Center
- State-level UI policies from the COVID-19 US State Policy Database

Contextual Data

- States' COVID-19 cases and deaths from the New York Times
- Vaccination rates from the Centers on Disease Control and Prevention
- State-level home price changes from the Urban Institute
- State-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics
- State-level business closures from CUSP

Research Design

Quantifying Community-Level Disparities

- Descriptive individual-consumer level regression analysis, with interacted and main effects for community composition and time

Explaining Community-Level Disparities

- Oaxaca-Blinder decomposition to test if the difference in community-level racial disparities in credit scores is due to common correlates of financial well-being or differences in wealth-building opportunities

Exploring Cohort Effects Across Economic Contexts

- Descriptive individual-consumer level regression analysis, with interacted and main effects for cohort and time (conducted on *matched* sample and community subsamples)

Policy Impact Analysis

- Staggered difference-in-difference design (TWFE) with controls for other policies, COVID-19 metrics, economic volatility, and business closures
- Robustness checks on sub-samples and contiguous counties

Key Variable Definitions

- **Credit scores**: the average VantageScore from 300 to 850, where scores below 600 are considered subprime.
- **Credit card delinquencies**: whether consumers who have at least one open credit card are 30 days or more past due on payments on at least one credit card.
- **Majority Black, Hispanic, and Native communities**: ZCTAs where 50 percent or more of residents identify as non-Hispanic Black, Hispanic, non-Hispanic Native American or American Indian, or non-Hispanic White.

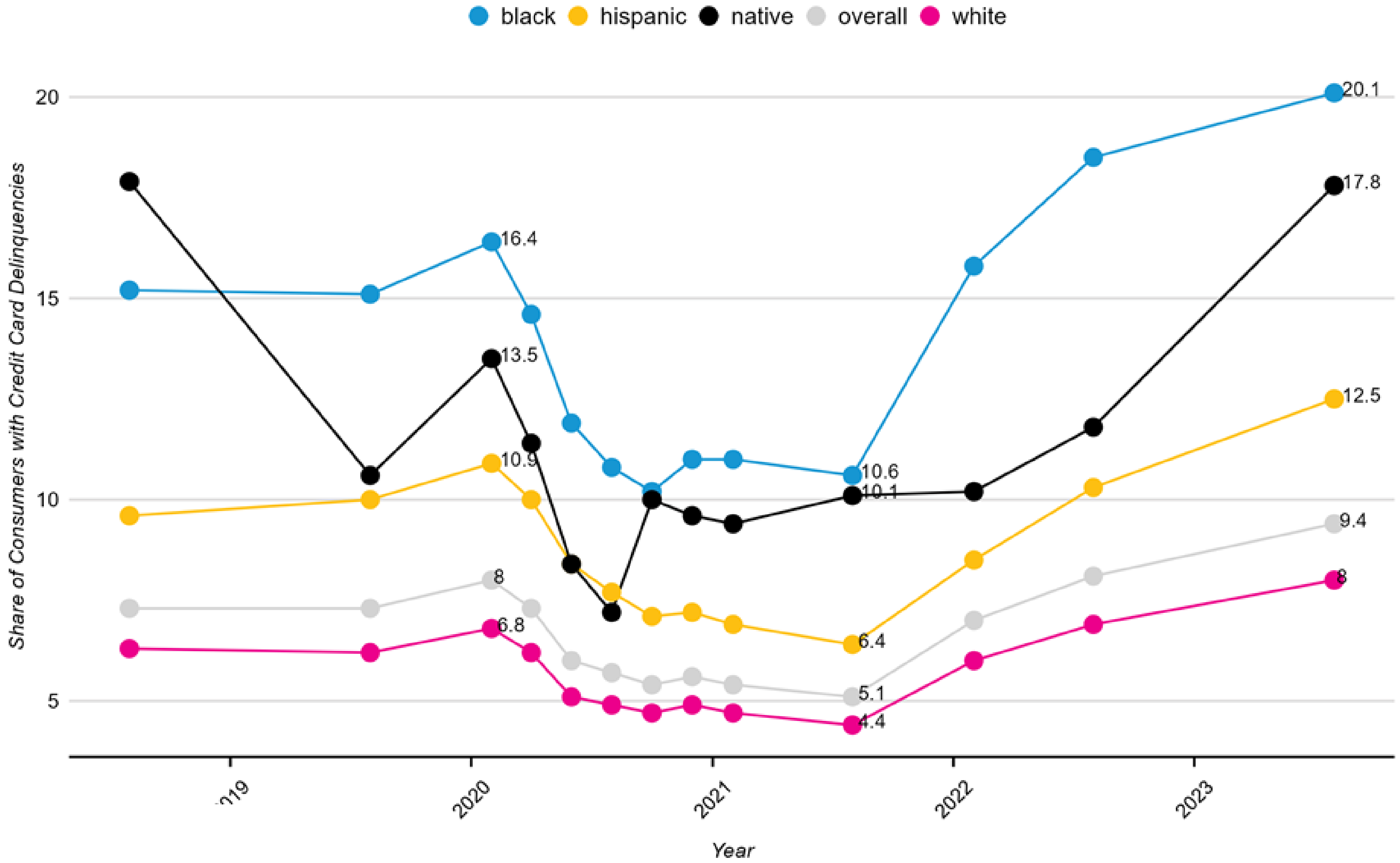
Key Takeaways

How did young adults' credit health change over the pandemic?

Did community-level racial disparities in credit health widen or narrow?

Credit Card Delinquencies Decline Rapidly in the First Year of the Pandemic Before Rising to Pre-Pandemic Levels

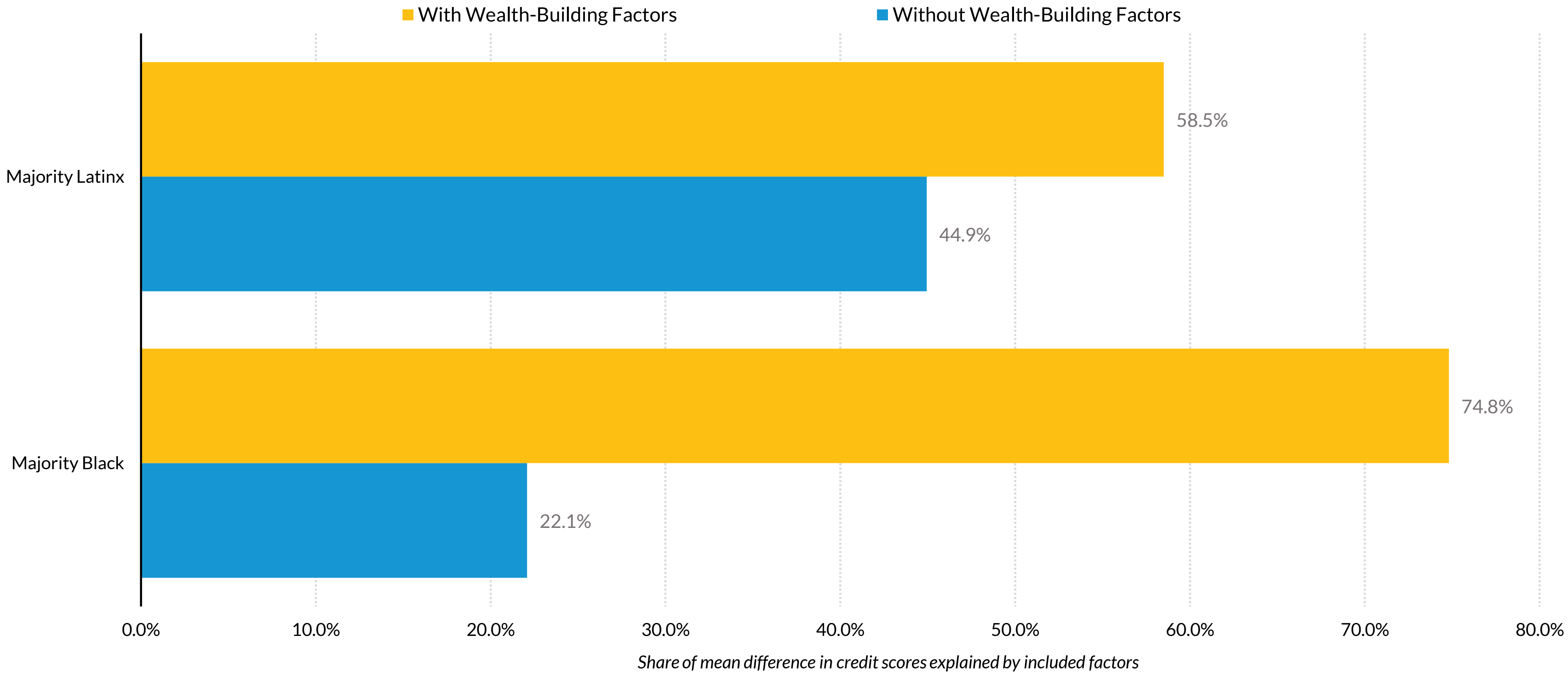
Share of young adults ages 20-29 with a delinquent credit card payment, among consumers with a credit card, by community demographic composition from 2018-2023; not regression-adjusted



To what extent do community-level factors associated with credit health and differences in wealth-building opportunities explain community-level racial disparities in young adults' credit scores?

Racial Disparities in Credit Scores Largely Due to Differences in Wealth-Building Opportunities

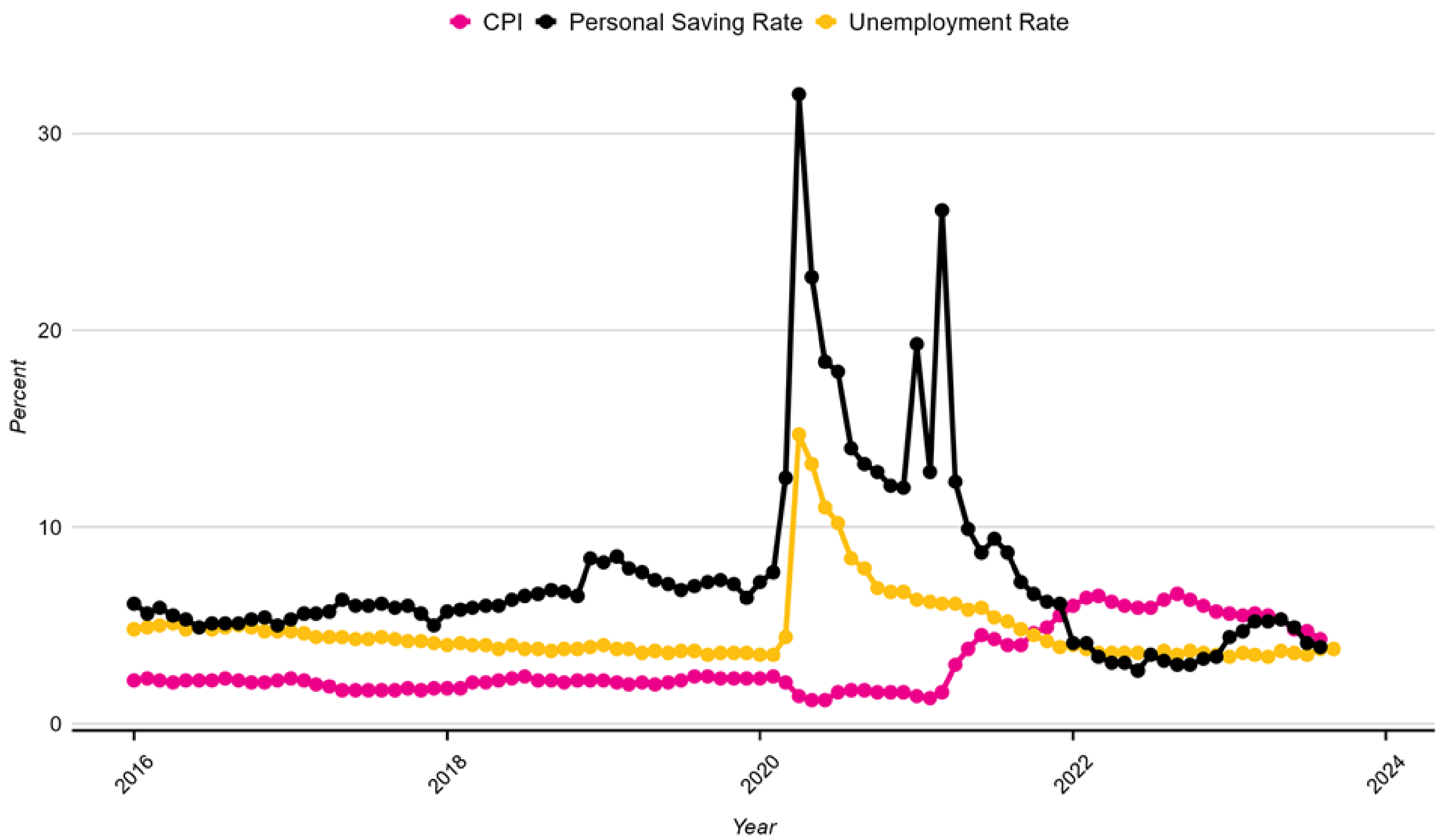
Share of the mean difference in young adults (20-29) credit scores across communities explained by included factors



How do young adults in 2020 fare relative to young adults in non-recessionary times, as measured by credit scores?

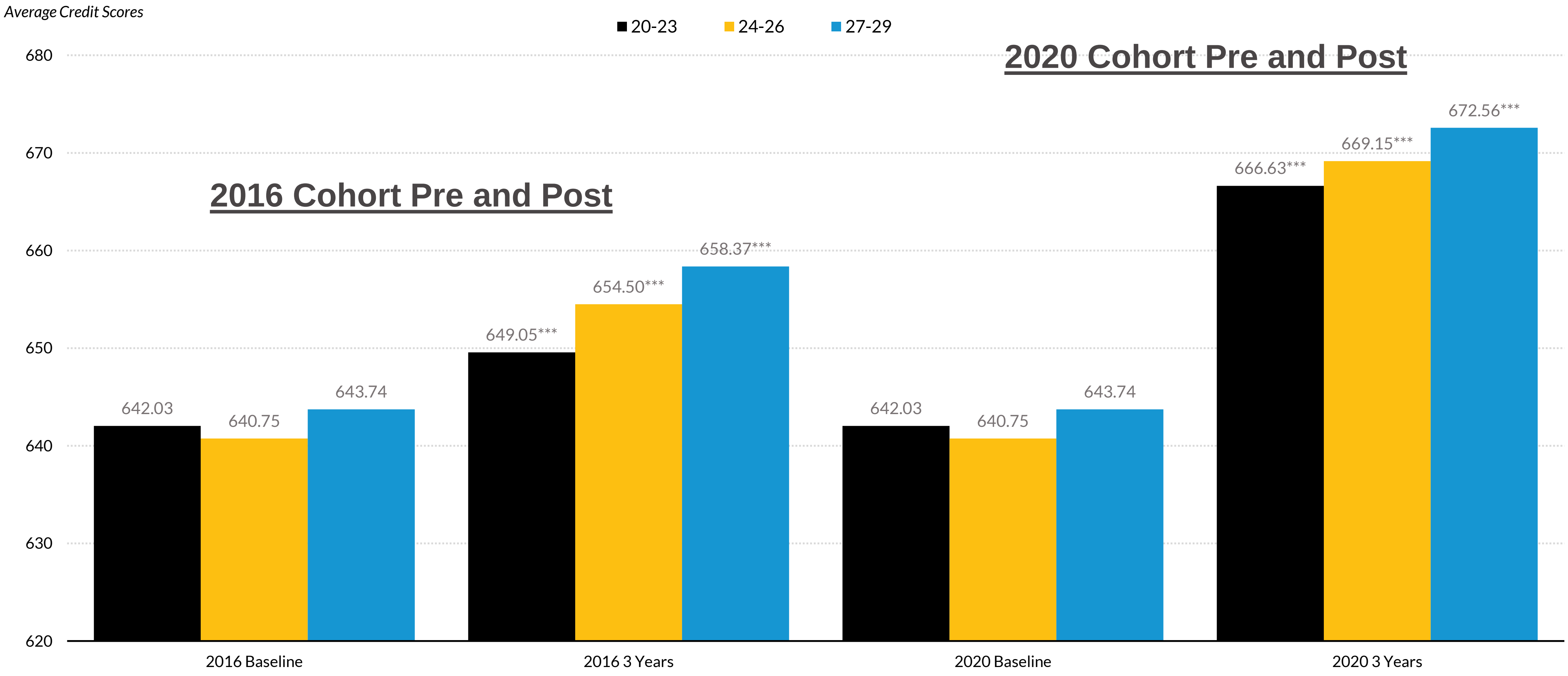
Greater Macroeconomic Volatility in 2020

Trends in inflation rate, personal savings rate, and unemployment from 2016 to 2023



Young Adults In 2020 See Larger Gains in Credit Scores

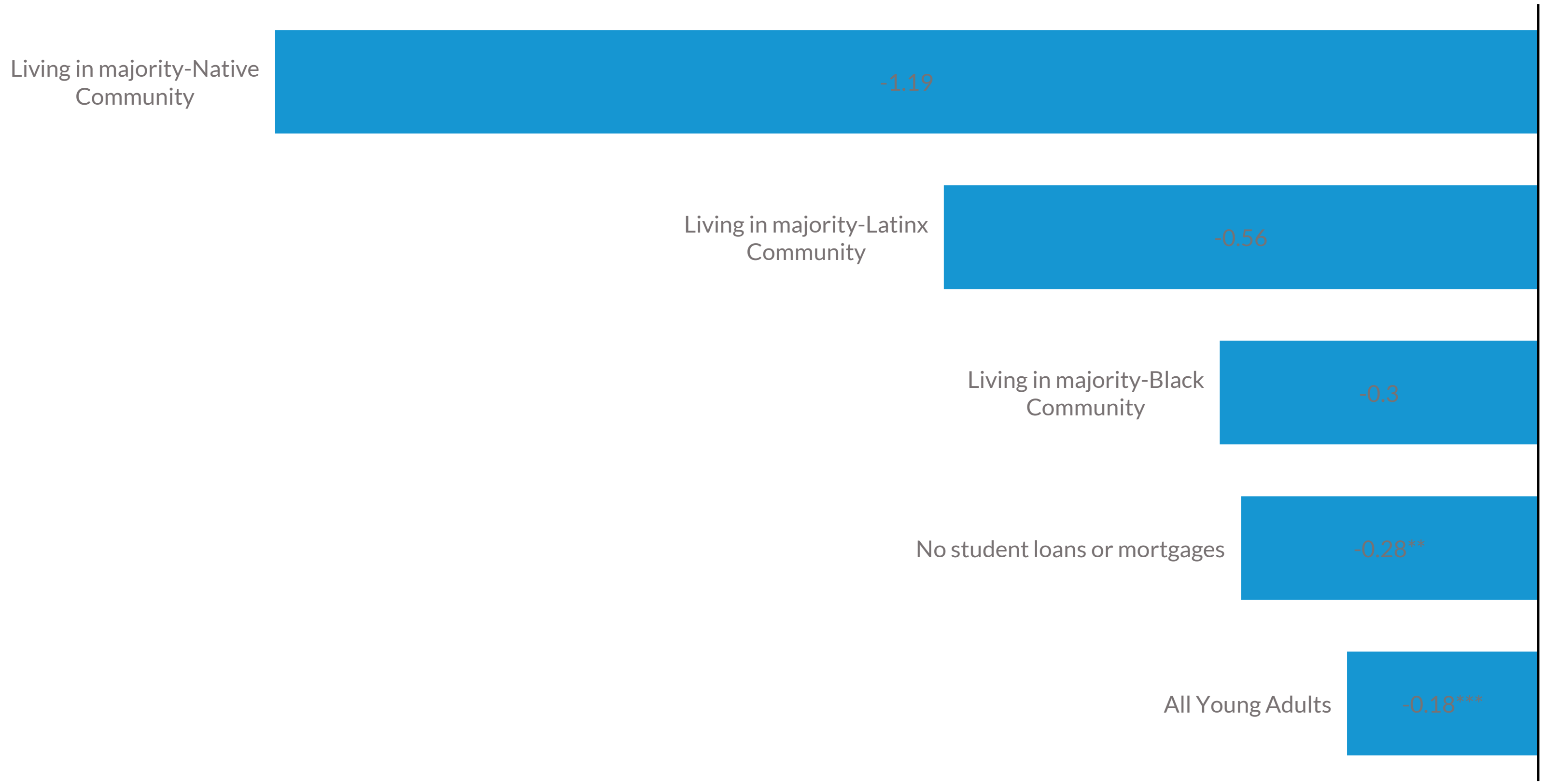
Average credit scores in the baseline year and three years later for the matched 2020 and 2016 cohort of young adults ages 20-23, 24-26, 27-29; regression-adjusted



To what extent have state policies protected the financial well-being of young adults (ages 20-29) living in communities of color during the pandemic?

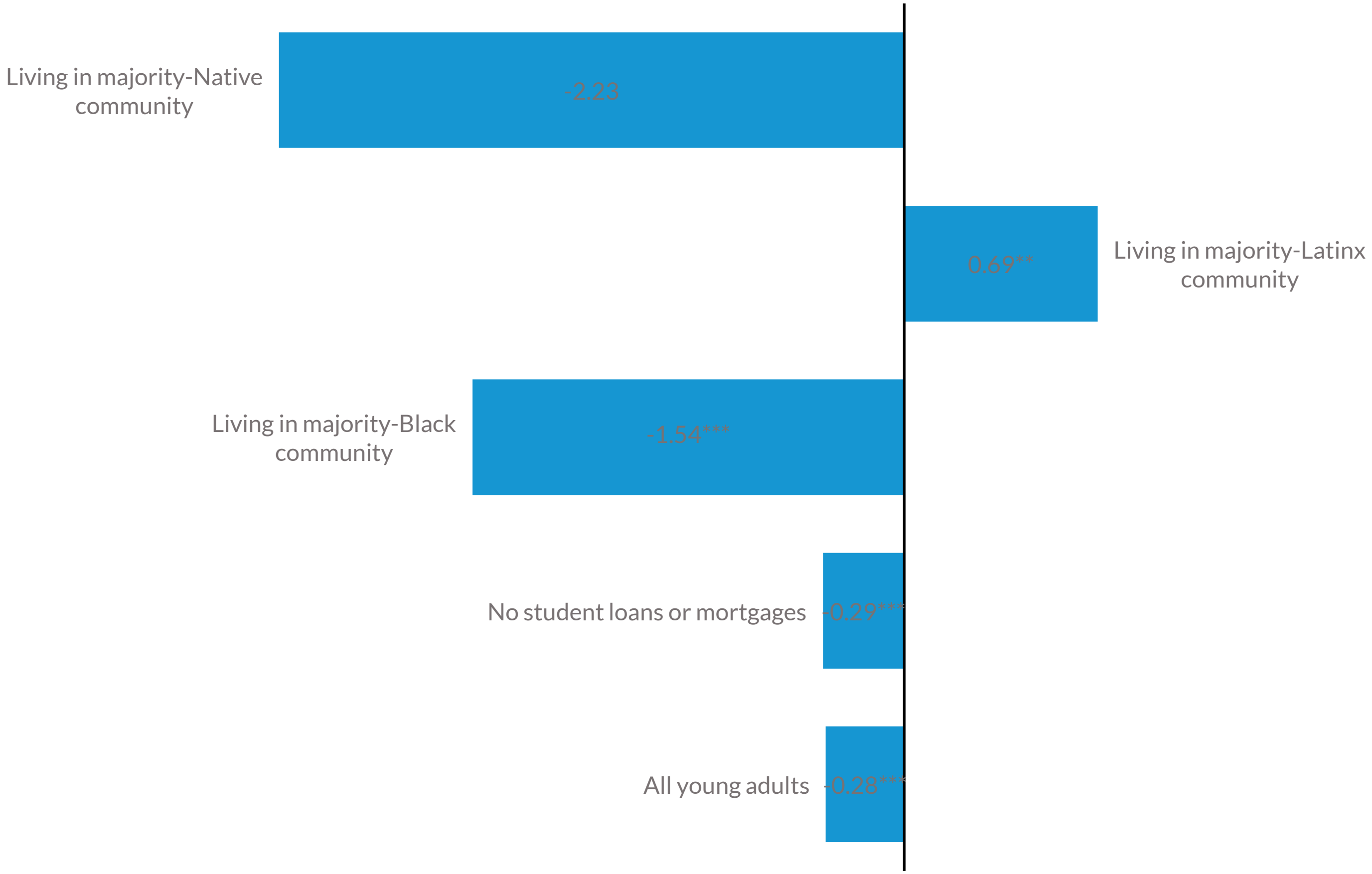
Utility Shutoff Moratoria Reduced Young Adults' Delinquencies

Percentage point changes in the share of young adults (ages 20 to 29) with a 30+ day late credit card bill after implementation of state-level utility shutoff moratoria, across different groups



Extended UI (13-week) Decreased Delinquencies for Young Adults in Communities of Color

Percentage point changes in the share of young adults (ages 20 to 29) with a 30+ day late credit card bill after implementation of state-level 13-week extended benefits UI programs, across different groups



Key Findings

- Young adults see improvements in credit health early in the pandemic, but these gains begin to reverse in 2022 and 2023– driving widening racial disparities across communities
- These pandemic-era gains in credit health early in the pandemic are larger in magnitude that gains observed in similar young adults in less economically volatile times– an unexpected finding
- State-level initiatives may have helped young adults' avoid deeper financial distress in the aftermath of the pandemic– although effects are relatively small
- Community-level racial disparities in credit can be largely explained by both differences in correlates of credit health (employment, income, etc.) as well as differences in wealth-building opportunities

Please contact kmartinchek@urban.org with any questions or comments or if you're interested in this work and want to collaborate or talk further.

Personal Website:

OLD -- Working Paper (SSRN):

Appendix Slides

Related Publications

- Working Paper (SSRN): Young Adults' Use of Debt and Credit During the Pandemic: Racial Disparities and the Effectiveness of State Initiatives to Protect Young Adults Living in Communities of Color
- Research Report: How Can States Help Young Adults Weather a Recession?
- Data Repository: Young Adults' Use of Debt and Credit During the COVID-19 Pandemic: Data Tables
- Blog: Young Adults Are Feeling the COVID-19 Recession's Effects Three Years Later, Especially in Communities of Color
- Full Dissertation (May 2024): Young Adults' Use of Debt and Credit During the COVID-19 Pandemic (link not yet available)
- Co-Authored Factsheet: What Can Policymakers Do to Help Young Adults Cope with Debt?: Credit Health Among Adults Ages 18 to 24
- Blog: New Data Show Inflation Could Undermine Families of Color's Financial Resilience. How Can Policymakers Help? (and Federal Reserve Seminar Recording)
- Blog: Young Millennials and Gen Zers Face Employment Insecurity and Hardship during the Pandemic

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For research support, mentorship, code advice, and more throughout this research project.

What do these findings mean for policy and practice? How can future research build on these insights?

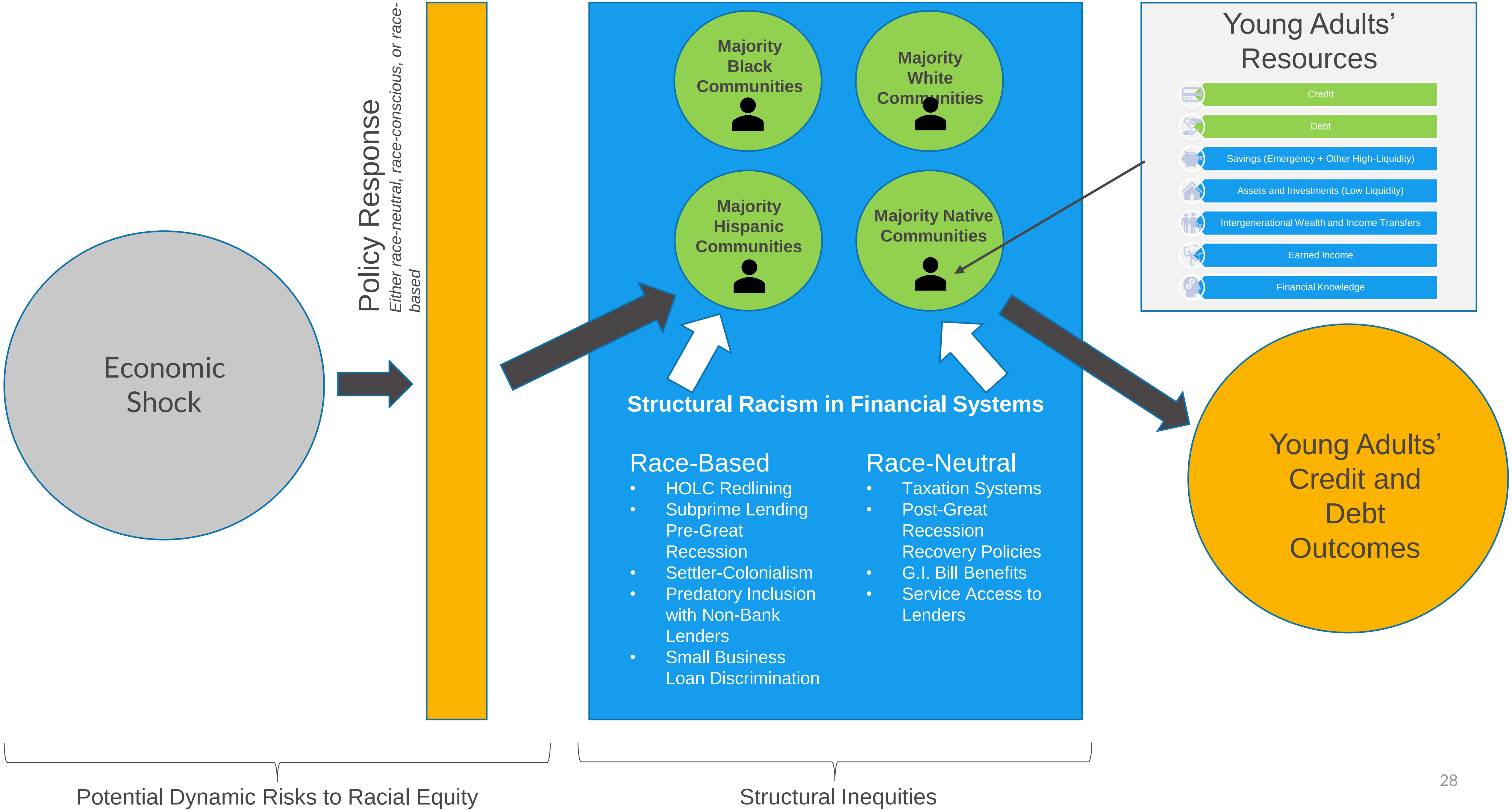
Future Directions for Research

- Disentangling individual and community outcomes
- Exploring trends in other financial outcomes
- Quantifying federal policy effects
- Comparing trends in other economic downturns

Policy Implications

- **Reduce community-level racial disparities in credit health**
  - Equalize access to credit across communities through place-based investments
  - Increase wealth of young adults of color
  - Address unequal returns to investments across communities
- **Insulate young adults against economic downturns**
  - Automatically increase eligibility and benefits level of automatic stabilizers

Theoretical Model and Limitations


Economic Shock
Policy Response
Either race-neutral, race-conscious, or race-based
Majority Black Communities
Majority White Communities
Majority Hispanic Communities
Majority Native Communities
Structural Racism in Financial Systems
Race-Based
• HOLC Redlining
• Subprime Lending Pre-Great Recession
• Settler-Colonialism
• Predatory Inclusion with Non-Bank Lenders
• Small Business Loan Discrimination
Race-Neutral
• Taxation Systems
• Post-Great Recession Recovery Policies
• G.I. Bill Benefits
• Service Access to Lenders
Young Adults' Resources
Credit
Debt
Savings (Emergency + Other High-Liquidity)
Assets and Investments (Low Liquidity)
Intergenerational Wealth and Income Transfers
Earned Income
Financial Knowledge
Young Adults' Credit and Debt Outcomes
Potential Dynamic Risks to Racial Equity
Structural Inequities

Delimitations of Empirical Analysis

Focuses on credit and debt outcomes, a subset of overall financial well-being

Focuses on the period from 2020 to 2023– which is distinct from other economic downturns

Examines outcomes among consumers with a credit record, which does not capture details on the approximately 11 percent of U.S. adults without a credit record

Examines race and ethnicity effects at the community level

Focuses on outcomes for consumers living in majority Black, Hispanic, and Native American communities

Limitations

Statistical Conclusion Validity

- Specification error in using community-level race
- Underpowered estimates for majority Native American communities

External Validity

- Specific period, outcomes, and population that may not be generalizable
- Sample represents consumers with a credit record, not all consumers

Multicultural Validity

- Race is measured at the community level
- No data on AAPI communities

Measurement Validity

- Measurement error in using community level operationalization of race
- No dosage differentiation on pandemic recession strength across communities
- Drawn from solely quantitative data, despite measuring multiple credit outcomes

Internal Validity

- Possible experimental mortality effects
- A volatile economic context provides many intervening effects beyond a recession
- Selection-maturation effects on credit health trends

Study Contributions

- Looking at credit health outcomes of young adults post-recession
- Examining heterogeneity in credit and debt trajectories post-recession across communities
- Disaggregating outcomes across multiple races and ethnicities at the community level
- Using a critical theory lens in interpreting findings to explore the behavior of consumers within communities (a micro-macro frame)
- Using a large-sample administrative dataset of credit bureau records for precise estimates
- Examining recessionary impacts in a new economic context—the pandemic recession using recent data

Data Details

Data Details: Credit Bureau Data

- The core dataset for the proposed dissertation is the Urban Institute's longitudinal database of five million individual consumers' credit records, which is a deidentified two percent random probability sample from a major credit bureau.

- In this dissertation project, data on consumers' credit records are linked to information on alternative financial service (AFS) loans from "a Fair Credit Reporting Act regulated agency whose unique data are derived from various financial service providers. AFS providers include online small-dollar lenders; online installment lenders; storefront small-dollar lenders; and single payment, line of credit, auto title, and rent-to-own lenders".

- The credit bureau data include zip-code-level identifiers for consumers, but not more granular geographic identifiers, nor demographic details (including individual consumers' gender, race, ethnicity, education, and income) beyond age. The credit bureau data sample is refreshed, meaning consumers new to the credit market enter the panel in proportion to the overall market. The panel of credit records is representative of consumers with a credit record at the national, state, and sub-state levels at a single point in time and is appropriate for examining changes over time.

- The data listed in this dissertation were processed as part of a larger project at the Urban Institute and then publicly published in the Urban Institute Data Catalog (see Martinchek, 2024 for data). All data tables and figures in this dissertation are drawn from Martinchek (2024), are cited accordingly in table and figure notes, and are publicly available. Per Urban's agreement with the data provider, data are suppressed when they reflect fewer than 50 consumers—meaning that if there were fewer than 50 consumers with credit card delinquencies living in a particular community, these data would not be presented.

Data Details: Credit Bureau Data Limitations

1. **No consumer-level characteristics beyond age:** The credit bureau data include zip code-level identifiers for consumers, but not more granular geographic identifiers, nor individual-level demographic details (including gender, race, ethnicity, education, and income) beyond consumer age. As such, I am unable to add additional individual-level controls for correlates of credit health, including income, education, employment, and asset ownership in any of the empirical estimates presented in this dissertation.

2. **Requires proxies for race and ethnicity:** The lack of individual administrative data on consumers' race and ethnicity is a significant challenge in this study and must be thoughtfully considered to bolster the trustworthiness of the results. To address this challenge, I use community-level racial and ethnic demographic data at the ZCTA level to augment the credit bureau data. In using community-level racial and ethnic demographic data, the analyses test for heterogeneous effects across community demographic compositions, not individual consumers.

3. **Not generalizable to all consumers:** Credit bureau and alternative financial services data do not include information on the 11 percent of the U.S. adult population who are credit invisible or do not have credit records. Of particular interest to this study: (a) younger adults are less likely to have credit records, with over 80 percent of 18- and 19-year-olds not having a credit record and (b) consumers are less likely to open credit accounts or seek out new credit during economic downturns. Further, Black and Hispanic consumers are more likely to be credit invisible compared with White or Asian consumers across all age groups Overall, this means that administrative data on consumer credit records do not generalize to all consumers.

Data Details: Credit Bureau Data + Community Level Race

- To identify communities of color, I categorize communities (operationalized at the ZCTA level) by the share of the population with the ZCTA that identifies as non-Hispanic Black, non-Hispanic Native American or American Indian (referred to as Native American throughout this dissertation), and Hispanic in the 5-year ACS (2015-2019). This matches a similar approach by Martinchek and colleagues (2022), where researchers using administrative credit bureau records also use ACS data to categorize communities based on racial and ethnic demographics.
- Further, given the substantial base of scholarship on the role of residential segregation in shaping individual consumers' financial outcomes, exploring the relationship between communities and the outcomes their residents face enables an interesting discussion of how longstanding dynamics of residential segregation and community context may leave young adults in those communities with fewer opportunities to build and preserve strong credit profiles—although direct testing of this relationship is out of scope of this dissertation study.
- The approach used in this dissertation study can be seen as a proxy measure of structural racism, as communities are one level on which structural racism operates and geographic measures have long been used to interrogate residential segregation's impact on individual-level outcomes. Further, geographic approaches are well-suited to quantify the magnitude of the impact of residential segregation and community-level context—which is one of the core research aims of this dissertation. Additionally, **taking a community-level approach pushes beyond disparities studies that reinforce our fixation on individual risks, responsibilities, and interventions to interrogate the factors that influence and structure individual resources and opportunities—like community context**.

Data Details: American Community Survey Data

- Because the credit bureau data do not contain details on individual consumer characteristics beyond consumer age and zip code of residence, I draw on Zip Code Tabulation Area (ZCTA) level data from the 2015-2019 American Community Survey (ACS) to enable empirical analyses.

- While zip codes are lines that reflect postal routes, ZCTAs are geographic areas that capture the coverage of postal routes and are used by the Census Bureau to present data at this level of geography. All measures drawn from the ACS do not change over time and are defined based on the consumer’s zip code of residence at baseline (February 2020 for research questions 1A, 1B, 2C, 2D; and either August 2016 or February 2020 for research questions 3A and 3B).

- I also use ACS data from the 5-year survey (2015-2019) at the ZCTA level to enable the use of the three-way Oaxaca-Blinder decomposition in chapter four of this dissertation. I use data on median household income (from table S1903), educational attainment (share with a bachelor’s degree or higher, from table S1501), employment status (share who are employed, from table S2301), and homeownership (share with a mortgage, from table B25027) at the ZCTA level disaggregated by age to answer RQ 1A. The exact age group definitions varied by ACS indicator but were merged onto the credit bureau data based on consumers’ ages and ZCTA of residence in the baseline period. To address missingness in the ACS data, ZCTA-level data on income, education, employment, and homeownership were mean-imputed within each relevant age group before being merged onto the credit bureau data.

Data Details: Mobility Metrics Data

- I also draw on data from Urban Institute's Mobility Metrics in 2018 at the county level to disaggregate differences in mean credit scores across communities into their contributing factors (RQ2's analysis).
- Specifically, I use data on: (1) the neighborhood exposure index, or the share of a person's neighbors who are people of other races and ethnicities, broken down by race and ethnicity (which is a proxy measure of residential racial diversity and segregation); and (2) the ratio of the share of a community's housing wealth held by a racial or ethnic group to the share of households of the same group, broken down by race and ethnicity for Black, Latinx, and white households.
- Since these are county-level measures, I weight these measures by the racial and ethnic composition of ZCTAs (from the ACS) to generate ZCTA-level estimates of residential segregation and housing wealth that I use in the final analysis.

Data Details: American Community Survey Data Imputation

- I use imputation to ensure all ZCTAs have values for all variables, as conducting the Oaxaca-Blinder decomposition requires complete case analysis. As such, for ZCTAs that did not have age-specific estimates for specific variables, I used the mean value for all ZCTAs for that particular ZCTA's variable value for each age group.

- Relatively few ZCTAs required mean imputation in the overall sample, except for age-specific median income variables for young adults. For ZCTAs with imputed data, standard errors may likely be underestimated, as is the case in all single imputations (Li et al., 2015). I expect that given the large sample size of my data; this is unlikely to be a challenge in detecting statistically significant effects.

Variable	Age Range	Share of ZCTAs with Non-Missing Data	Number of ZCTAs Missing	Mean
Bachelor's Degree	18-24	92.5	2,453	9.8 percent
Bachelor's Degree	25-34	94.5	1,799	26.6 percent
Employment Status	20-24	90.5	3,131	76.7 percent
Employment Status	25-29	91.2	2,891	81.1 percent
Median Income	15-24	40.1	19,828	$42,123
Median Income	25-44	82.2	5,875	$70,682

Data Structure: Research Question 1 and 2

Data Extract Number	Data Extract Month	Alternative Financial Services Data Available?
1	August 2018	No
2	August 2019	No
3	February 2020	Yes
4	April 2020	Yes
5	June 2020	Yes
6	August 2020	Yes
7	October 2020	Yes
8	December 2020	Yes
9	February 2021	Yes
10	August 2021	No
11	February 2022	No
12	August 2022	No
13	August 2023	No

Data Structure: Research Question 3

Cohort	Period	Data Extract Month	Ages of Cohort Members		
			20-23 at Baseline	24-26 at Baseline	27-29 at Baseline
Non-recession	Baseline: Year 0	August 2016	20-23 years old	24-26 years old	27-29 years old
Non-recession	Year 1	August 2017	21-24 years old	25-27 years old	28-30 years old
Non-recession	Year 2	August 2018	22-25 years old	26-28 years old	29-31 years old
Non-recession	Year 3	August 2019	23-26 years old	27-29 years old	30-32 years old
Pandemic Recession	Baseline: Year 0	February 2020	20-23 years old	24-26 years old	27-29 years old
Pandemic Recession	Year 1	February 2021	21-24 years old	25-27 years old	28-30 years old
Pandemic Recession	Year 2	February 2022	22-25 years old	26-28 years old	29-31 years old
Pandemic Recession	Year 3	August 2023	23-26 years old	27-29 years old	30-32 years old

Other Variables Used in this Study

- **Auto and retail loan delinquencies**: In this study, I measure whether consumers who have an open auto or retail loan are 60 days or more past due on payments.
- **Credit card utilization:** Credit card utilization captures the share of available credit consumers are currently using and higher rates of credit card utilization may indicate that consumers have emergency financial needs they are covering through borrowing or can indicate that they have low levels of buffers to respond to financial emergencies, should one emerge. In this study, I measure the share of available credit card credit used among consumers with at least one open credit card. This is measured and aggregated across all open credit cards.
- **AFS loan use:** Alternative financial services loans often have “short repayment periods, large, required payments, and high prices, making them difficult to repay and potentially damaging to consumers’ financial well-being” (Martinchek & Johnson, 2023, pp. 1). These products are often a “lender of last resort”, used when consumers have run out of alternative options. Research by the Consumer Financial Protection Bureau (2017) suggests that AFS loans may help consumers in discrete, short-term circumstances but may cause long-term damage if used frequently or for long periods of time (Consumer Financial Protection Bureau, 2017). In this study, I measure use of AFS loans across a range of non-bank lenders, including short-term unsecured loans (such as payday loans), loans where personal property was used as collateral (such as auto title loans), or transactions under which property was leased in exchange for a weekly or monthly payment with the option to purchase (rent-to-own) from online small-dollar lenders; online installment lenders; storefront small-dollar lenders; and single payment, line of credit, auto title, and rent-to-own lenders.

Regression Specifications

Regression Specification: RQ 1

$$Y_{izt} = \alpha_1 Community_{iz} + \alpha_2 Community_{iz} \times \theta_t + \theta_t + u_{izt}$$

Here, Y_{it} represents the credit or debt outcome of interest of young adult i in ZCTA z period t, α_1 is the effect of living in a community of color in February 2020, α_2 allows for the time trend in the outcome variable to vary based on whether or not a consumer lives in a community of color in February 2020, θ_t represents time fixed effects and u_{izt} is the heteroskedastic-robust error term, which is clustered at the ZCTA level.

This specification is run separately for each credit outcome of interest (credit scores, credit card utilization, credit card delinquencies, auto and retail loan delinquencies, and AFS loan use) and will be run separately for majority Black, Hispanic, and Native American communities.

Regression Specification: Phase 1 Oaxaca-Blinder

$$W_{1izt} = \delta_{1t} + \beta_{1t} X_{1zt} + \phi_{1izt}$$

$$W_{2izt} = \delta_{2t} + \beta_{2t} X_{2zt} + \phi_{2izt}$$

where W_{1izt} and W_{2izt} are the credit score of young adult i in ZCTA z in group 1 and 2 at time t (February 2020), δ_{1t} and δ_{2t} are constants, X_{1zt} and X_{2zt} are vectors of correlates of credit health (including median income, educational attainment, employment status, and homeownership) *measured at the ZCTA level*, β_{1t} and β_{2t} are vectors of regression coefficients for the correlates of credit health. These coefficients are assumed to vary by group but not by time. ϕ_{1izt} and ϕ_{2izt} are the error terms.

Regression Specification: Phase 2 Oaxaca-Blinder

$$\Delta\overline{W} = \sum_{i=1}^{k} \beta_{1t}\,(\bar{X}_{1t} - \bar{X}_{2t}) \underline{+}\text{-} \sum_{i=1}^{k} \bar{X}_{1t}\,(\beta_{1t} - \beta_{2t}) - \sum_{i=1}^{k} (\bar{X}_{1t} - \bar{X}_{2t})\,(\beta_{1t} - \beta_{2t})$$

Here, $\Delta\overline{W}$ reflects the difference in mean credit scores between group 1 (young adults living in majority White communities) and group 2 (young adults living in communities of color—majority Black, Hispanic, and Native American communities), *from the perspective of group 1*. Here, the entire decomposition is done from the perspective of group 1—and importantly, results will depend on the choice of reference group when conducting the decomposition. Superscripts 1 and 2 denote which group the term refers to, i denotes an individual consumer, $\bar{X}$ refers to averages of the covariates and β reflects coefficients estimated in Equation 3.2. $\sum_{i=1}^{k} \beta_{1t}\,(\bar{X}_{1t} - \bar{X}_{2t})$ captures the portion of the difference in mean credit scores explained by differences in the average of covariates included in the decomposition between the two groups, where covariates are measured at the *community-level*. $\sum_{i=1}^{k} \bar{X}_{1t}\,(\beta_{1t} - \beta_{2t})$ captures the differential effect of these covariates (e.g., differences in returns to endowments) and “general effect of unknown factors” (Rahimi & Hashemi Nazari, 2021, pp. 11). This term is often regarded as the “unexplained” portion of the difference in means. $\sum_{i=1}^{k} (\bar{X}_{1t} - \bar{X}_{2t})\,(\beta_{1t} - \beta_{2t})$ captures the “interaction caused by the simultaneous group differences in the covariates level and their coefficients” (Rahimi & Hashemi Nazari, 2021, pp. 5).

Regression Specification: RQ 3

$$Y_{izt} = \alpha_1 Cohort_{iz} + \alpha_2 Cohort_{iz} \times \theta_t + \alpha_3 \theta_t + u_{izt}$$

Here, Y_{izt}represents the weighted credit score of consumer i in ZCTA z period t using the weights generated in the exact matching process, α_1 is the effect of being in the 2020 cohort at baseline in February 2020, α_2 represents average changes in credit scores one and two years after baseline for the 2020 cohort (relative to the 2016 cohort), α_3 represents average changes in credit scores one, two, and three years after baseline in the 2016 cohort, and $u_{izt}$is the heteroskedastic-robust error term, which is clustered at the ZCTA level and is adjusted for the matching weights.

This specification is run on three different matched samples of young adults: young adults ages 20-23, 24-26, and 27-29 years old in the baseline period for each cohort.

Regression Specification: RQ 3 Subgroup Analysis

$$Y_{izt} = \alpha_1 Community_{iz} + \alpha_2 Community_{iz} \times \theta_t + \theta_t + u_{izt}$$

Here, Y_{izt} represents the weighted credit score of young adult i in ZCTA z period t using the weights generated in the exact matching process, α_1 is the effect of living in a community of color at baseline (August 2016 or February 2020), α_2 allows for the time trend in the outcome variable to vary based on whether or not a consumer lives in a community of color at baseline (August 2016 or February 2020), θ_t represents time fixed effects and $u_{izt}$is the heteroskedastic-robust error term, which is clustered at the ZCTA level and is adjusted for the matching weights.

This specification is run on three different matched samples of young adults: young adults ages 20-23, 24-26, and 27-29 years old in the baseline period for each cohort.

Regression Specification: RQ 4

$$Y_{icst} = \gamma_t + \delta_c + \beta Policy_{st} + \beta X_{icst} + \epsilon_{icst}$$

Where Y_{icst} is the credit or debt outcome of interest for consumer *i* residing in county c in state *s* in period *t.* Throughout the analysis, I characterize an individual's state and county of residence based on the consumer's home address in February 2020 to account for the potential endogeneity of migration decisions as a response to the policy implementation; γ_t includes year-month fixed effects; and δ_c includes county fixed effects—while in some specifications, I use individual-fixed effects. $Policy_{st}$ are indicators for whether the state *s* had the policy active (utility shutoff moratoria or extended benefits UI programs (13 and 20 week)) in period t. X_{ist} is a large set of individual, state, and county-level controls. At the individual level, this vector of controls includes age and age squared. At the state level, I include COVID-19 vaccination rate (population 18+), number of COVID-19 cases per capita and the number of COVID-19 deaths per capita, unemployment rate, the share of UI payments out within three weeks, indicators for whether states had closure orders for restaurants, bars, movie theatres, gyms, and child care centers, indicators for whether states had active suspensions on vehicle repossessions and garnishments, an indicator for whether states had active Pandemic Unemployment Assistance programs, and an indicator for whether states had an active eviction moratorium in each period. Standard errors are clustered at the state level. By using individual consumer-level fixed effects, I controlled impact estimates for a consumer's credit history, improving the estimates' precision. The model with individual fixed effects and policy and contextual controls is the preferred model, aligning with work by Andre and colleagues (2024, 2023). My preferred specification includes controls and individual consumer-level fixed effects.

Sample Characteristics

Sample Age Breakdown

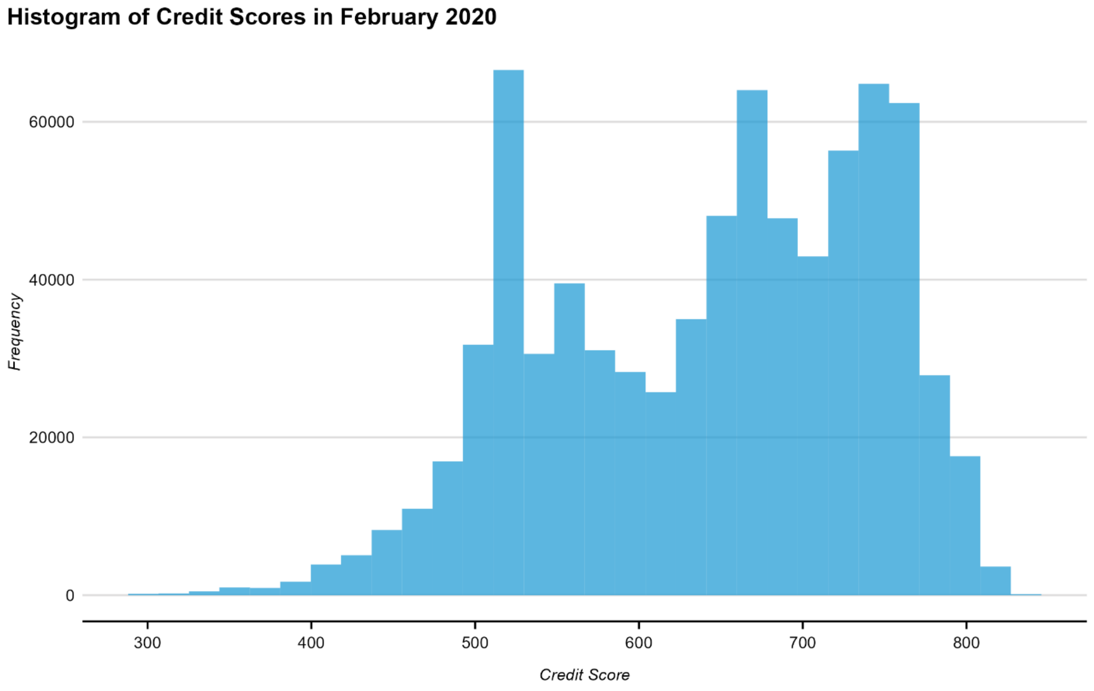
Age	Share of the Sample in this Age
20	7.76
21	8.49
22	9.06
23	9.65
24	10.03
25	10.4
26	10.72
27	11.03
28	11.27
29	11.61

Sample Community of Residence Breakdown

Community	Share of Consumers Living in this Community	Number of Consumers Living in this Community
Majority Black Community	6.12	49,352
Majority Hispanic Community	11.53	92,965
Majority Native American Community	0.14	1,156
Majority White Community	63.91	515,423

Sample Credit Characteristics

Indicator	Majority Black	Majority Hispanic	Majority Native American	Majority White
Average Credit Score	598.4	631.5	588.9	662.6
Share with a Student Loan	37.8	24.7	21.8	34.7
Share with a Credit Card	40.2	51	24.1	57.8
Share with an Auto Loan	30.5	37.1	35.7	38.7
Share with an AFS Loan	4	4.1	5.1	2.3
Share with a Mortgage	4.2	5.7	1.9	11.7



Robustness Checks

Robustness Check 1: Choice of Cutoff

- To inform the selection of this cutoff and test for sensitivity of findings across a range of community racial and ethnic demographics, I conduct my analyses for research questions 1A, 1B, and 3B across three different community demographic compositions: 30 percent, 50 percent, and 80 percent of residents who identify as Black, Hispanic, or Native American.
- In these checks, I found that using a 50 percent threshold would not produce disparate findings across other community demographic composition cutoffs. Largely, there was consistency in substantive results across the 30 percent, 50 percent, and 80 percent cutoffs for Black, Hispanic, and Native American communities; with results that generally became more striking as communities became more racially and ethnically diverse

Robustness Check 2: Controls

- The credit bureau data do not include individual-level covariates beyond age and zip code of residence, so it is not possible to control for additional individual demographic characteristics. Further, adjusted R-squared values remain low and suggest potential remedies to bolster explanatory power.
- To test remedies for additional explanatory power, I ran specifications of Equation 3.1 with (a) individual fixed effects, and (b) county-level fixed effects (separately).
- In running these robustness checks, I find that adding either form of fixed effects improves explanatory power substantially, as measured by adjusted R-squared values (increasing them to over 0.8 in most cases), while not changing the direction of overall substantive findings and only adjusting the coefficient estimates marginally compared with the specification without any fixed effects.

Robustness Check 3: Experimental Mortality

Period	Number of Consumers from February 2020	Share of Consumers from February 2020 that Remain in the Sample
February 2020	806,511	100
April 2020	798,495	99.01
June 2020	792,621	98.28
August 2020	786,651	97.54
October 2020	782,356	97.01
December 2020	778,164	96.49
February 2021	774,186	95.99
August 2021	763,545	94.67
February 2022	752,878	93.35
August 2022	747,735	92.71
August 2023	738,362	91.56

Robustness Check 4: Non-Imputed OB (Majority Black)

	Non-Imputed	Imputed
Mean Credit Score for Majority White Communities	652.1405	652.2485
Mean Credit Score for Majority Black Communities	585.1624	585.1771
Difference in Means	66.9781	67.07143
Difference in Means Due to Endowments	16.59673	14.81388
Difference in Means Due to Coefficients	46.50255	48.14564
Difference in Means Due to Interactions	3.878815	4.11191

Robustness Check 4: Non-Imputed OB (Majority Hispanic)

	Non-Imputed	Imputed
Mean Credit Score for Majority White Communities	652.1405	652.249
Mean Credit Score for Majority Black Communities	619.1455	618.695
Difference in Means	32.99507	33.5537
Difference in Means Due to Endowments	17.03611	15.1069
Difference in Means Due to Coefficients	14.45586	16.8236
Difference in Means Due to Interactions	1.503104	1.62327

Robustness Check 4: Non-Imputed OB (Majority Native)

	Non-Imputed	Imputed
Mean Credit Score for Majority White Communities	652.1405	652.249
Mean Credit Score for Majority Black Communities	578.8397	577.211
Difference in Means	73.30078	75.0375
Difference in Means Due to Endowments	36.05808	36.7736
Difference in Means Due to Coefficients	50.1701	52.1386
Difference in Means Due to Interactions	-12.9274	-13.875

Robustness Check 5: Sensitivity of Policy Impacts

- To complement the impact analysis, I conducted several robustness checks designed to build confidence in the direction and magnitude of policy impacts. In these checks, I did the following:
  - estimated policy impacts among the sample of consumers living in bordering counties of states that did and did not implement the policy of interest during the period;
  - quantified the impacts of policies on consumers who did not benefit from federal-level student loan and mortgage forbearance programs—or consumers who did not have student loans or mortgages in February 2020; and
  - quantified policy impacts within a set of paired contiguous counties, comparing states that implemented policies in the period with those that did not.

Robustness Check 5: Sensitivity of Policy Impacts

Finally, I used policy discontinuities at county borders to identify the causal effects of policies following similar approaches as Dube, Lester, Reich (2010) and Schmidt, Shore-Sheppard, and Watson (2020). To perform this analysis, I restructured the data so each county was observed once per period per adjacent pair. This restructuring was necessary so that observations could be assigned a vector of county pair-time fixed effects that allowed the adjacent border county to serve as a counterfactual. I tested several different sets of fixed effects: (1) county-level fixed effects only; (2) pair-time fixed effects only; and (3) county-level and pair-time fixed effects (preferred specification for this robustness check).

Robustness Check 5: Sensitivity of Policy Impacts

I used the following model:

$$Y_{ict} = \beta_1 Policy_c + \beta_2 X_c + \gamma_{pt} + \varepsilon_{ist}$$

In this model, Y_{icst} is the outcome of young adult (age 20 to 29) *I*, living in border county *c* in period t. $Policy_c$ is an indicator for whether the adult's county c of residence implemented the policy (utility shutoff moratoria or extended benefits UI programs (13 and 20 week)).X_c includes a robust set of controls, including COVID-19 vaccination rate (population 18+), number of COVID-19 cases per capita and the number of COVID-19 deaths per capita, unemployment rate, the share of UI payments out within three weeks, indicators for whether states had closure orders for restaurants, bars, movie theatres, gyms, and child care centers, indicators for whether states had active suspensions on vehicle repossessions and garnishments, an indicator for whether states had active Pandemic Unemployment Assistance programs, and an indicator for whether states had an active eviction moratorium in each period.γ_{pt} is a pair-specific time effect (in the preferred specification this captures the pair-time and county-level fixed effects, although as noted above, I also test this with county-level fixed effects and pair-time fixed effects). Standard errors are clustered at the state *s* level. This specification is run separately for each policy of interest, based on the contiguous county pairs for that policy in each period.

Matching Details

Matching Procedures

- I matched consumers in 2020 to consumers in 2016 using exact matching on baseline age and credit score to address possible selection bias between cohorts.
- I perform exact matching for three samples: young adults ages 20-23, 24-26, and 27-29 at baseline.
- Exact matching creates subclasses of young adults' age and credit score and assigns observations to each subclass, dropping subclasses that do not have observations from both the 2020 and 2016 cohorts (Stuart et al., 2011).
- Given the large sample size of my study, I can use exact matching—which has the advantage of not requiring assumptions on (a) the treatment or outcome model nor (b) the method of removing confounding from measured variables because the distributions of variables used for matching are exactly balanced (Stuart et al., 2011).

Matching Causal Inference Assumptions

- Causal inference is about trying to eliminate selection bias to recover the causal effect (e.g., ATE, ATT, MTE, etc.) but can only do so under certain conditions.
- Selection bias means that the outcome mean is different for the treatment and comparison groups.

Conditions under which matching can generate causal impact estimates:

- **Conditional independence assumption**: where treatment (here, cohort membership) assignment is *conditionally* random on a set of covariates—i.e. selection is based on observables. Under this assumption, the expected values of treatment and comparison groups are equal for each covariate. Also stated as: there is a set of known and quantified confounders that after adjusting for them, treatment assignment is independent of potential outcomes.
- **Common support**: For ranges of X (matching covariates) there is a positive probability of being both treated and untreated—there exists units in the treatment and comparison groups with the same values of X for every specific combination of the conditioning set. **This does not require covariate balance between the two groups– just positive probability**

Why Don’t I Present Matching Estimates As Causal?

- If you fail to control for all the covariates you need to– or covariates that influence “assignment” into cohort and the outcome (credit scores)– then you will get selection bias and not meet the conditional independence/unconfoundedness assumption.
- Although I create balanced groups using exact matching (see later slides) – where for all covariate combinations (age and credit score), there is common support across cohorts– it is likely I don’t fully meet the conditional independence assumption due to unobservables.
- Also, presenting the cohort analysis as causal is not meaningful from a policy perspective, as these estimates would capture the bundled effect of cohort membership– including variations in policy interventions, macroeconomic influences, and other factors that vary over time and impact young adults’ credit scores. As such, they would not be useful in understanding why young adults experience different credit score trajectories across cohorts.
- And my research question is not framed as a causal question– but a descriptive cohort comparison.

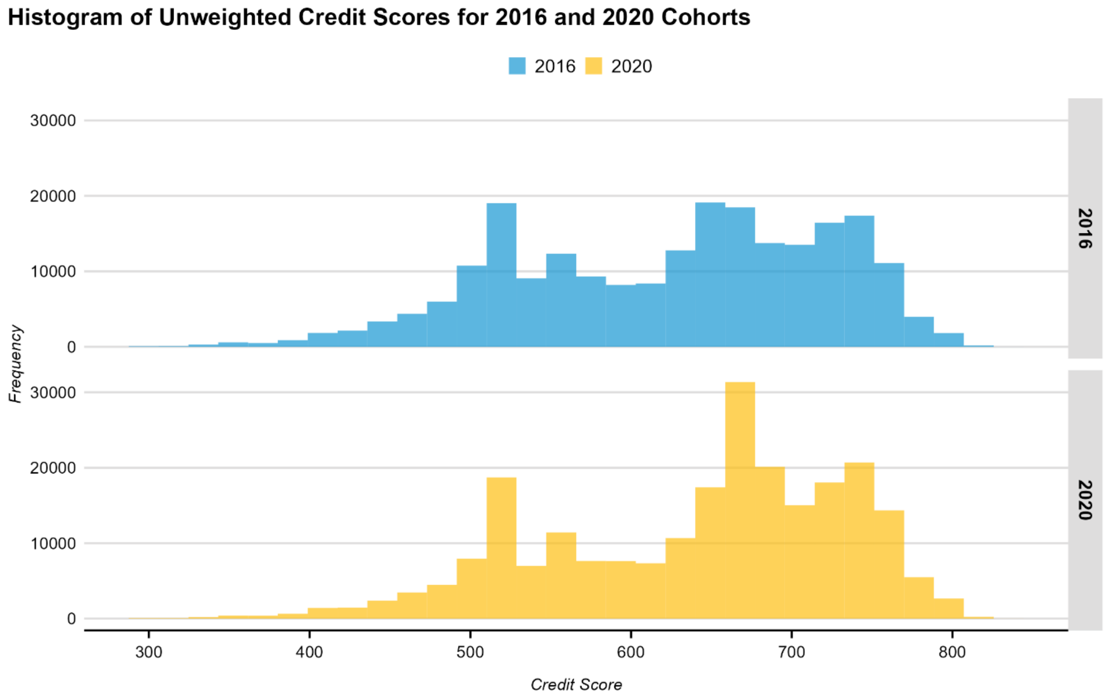
Observations Matched and Unmatched

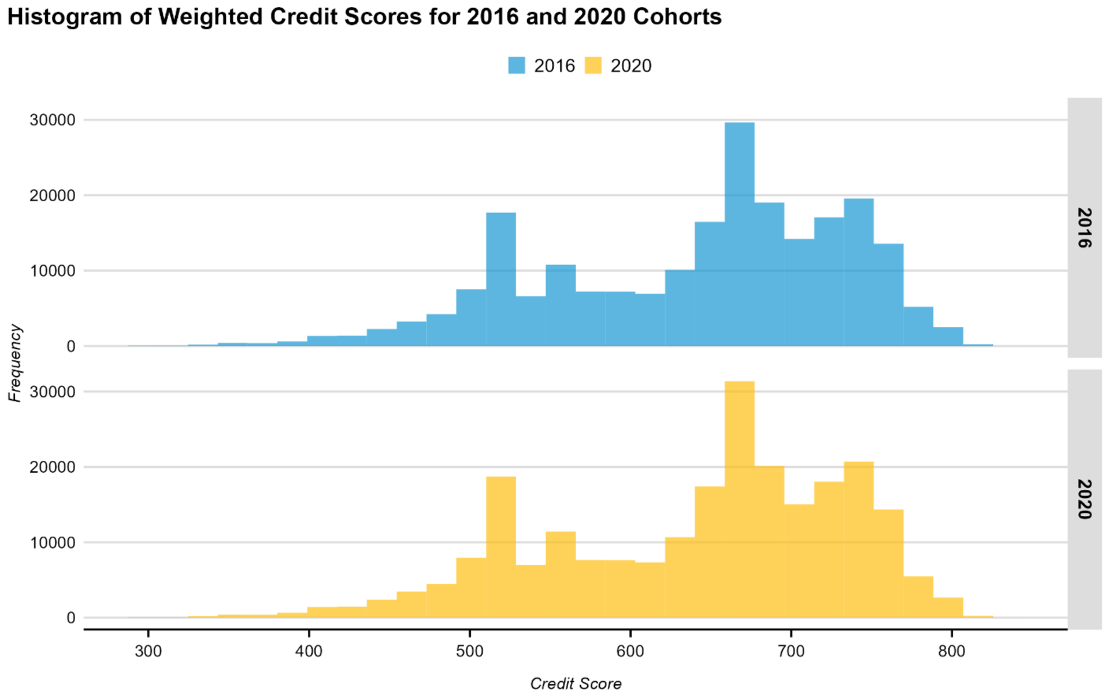
	Young Adults Ages 20-23	Young Adults Ages 24-26	Young Adults Ages 27-29
Number of Observations in Unmatched 2016 Cohort	240,279	260,702	254,819
Number of Observations in Unmatched 2020 Cohort	257,923	250,858	273,299
Number of Observations in Matched 2016 Cohort	225,613	254,830	250,284
Number of Observations in Matched 2020 Cohort	238,517	243,787	266,804
Percent Removed Between Matched and Unmatched Samples for 2016 Cohort	6.2	2.3	1.8
Percent Removed Between Matched and Unmatched Samples for 2020 Cohort	7.6	2.9	2.4

Matched and Unmatched Credit Scores

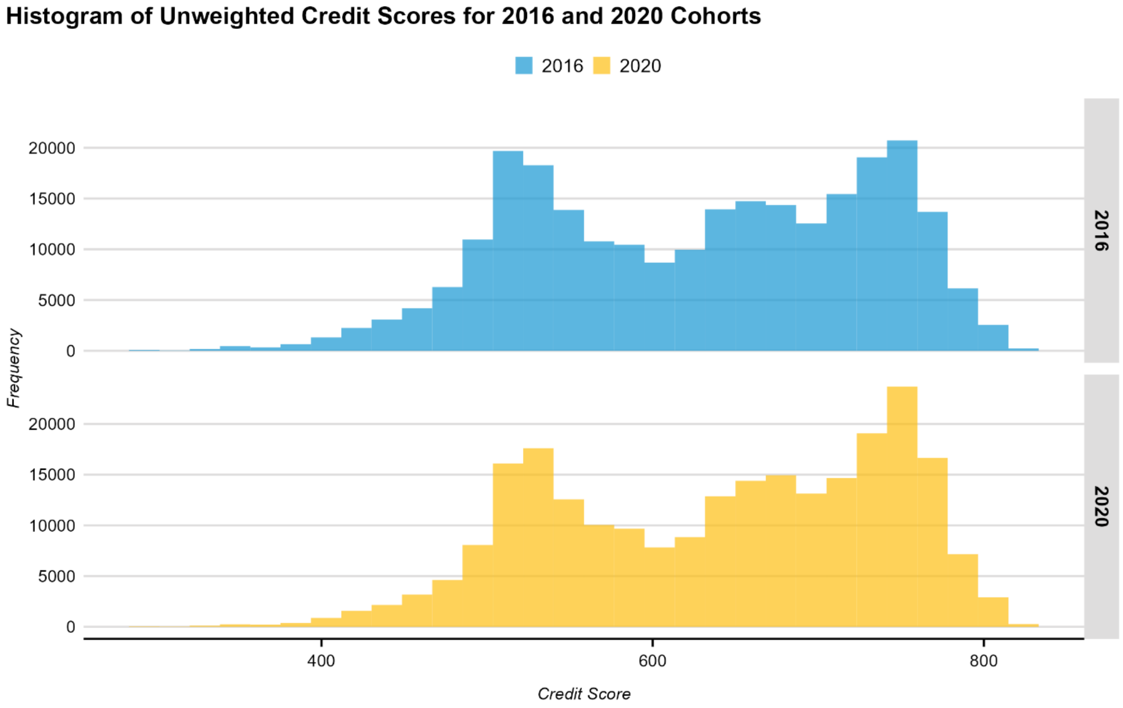
	Young Adults Ages 20-23		Young Adults Ages 24-26		Young Adults Ages 27-29	
	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
2016 Cohort: Baseline	642.0	624.9	640.8	628.1	643.7	636.5
2016 Cohort: 1 Year	642.6	628.4	644.5	633.3	648.6	642.1
2016 Cohort: 2 Years	646.0	633.4	650.1	639.7	654.1	648.0
2016 Cohort: 3 Years	649.6	637.9	654.5	644.5	658.4	652.5
2020 Cohort: Baseline	642.0	642.0	640.8	640.8	643.7	643.7
2020 Cohort: 1 Year	655.6	655.6	656.3	656.3	660.0	660.0
2020 Cohort: 2 Years	660.9	660.9	662.2	662.2	666.0	666.0
2020 Cohort: 3 Years	666.6	666.6	669.2	669.2	672.6	672.6

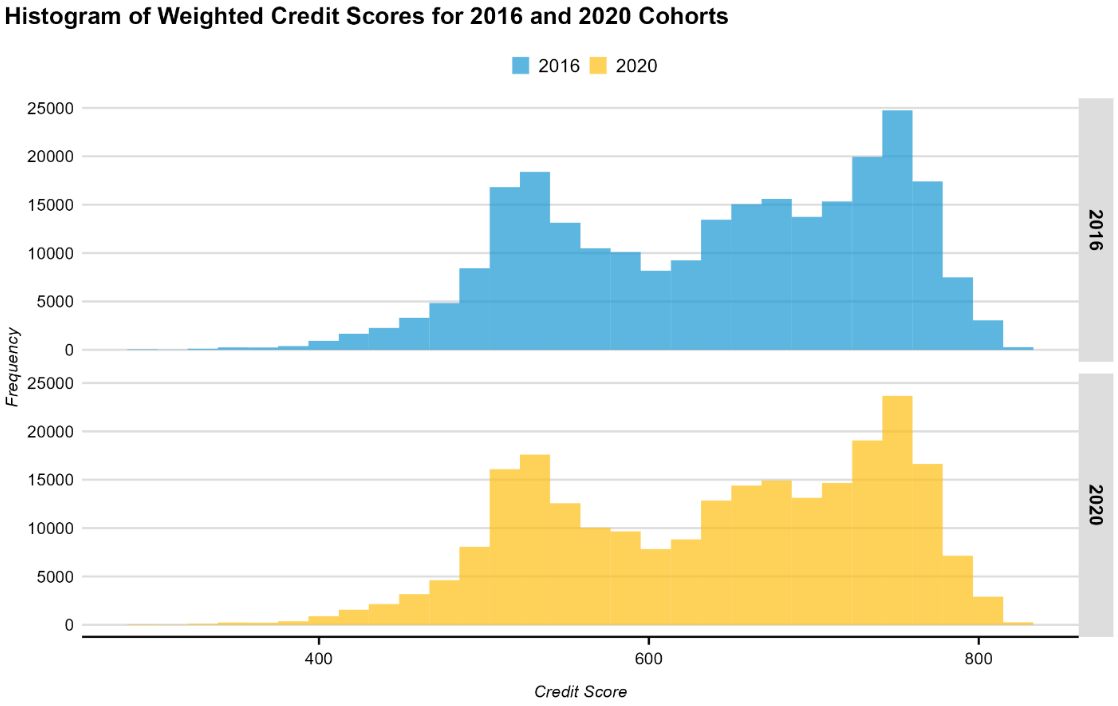
Matched and Unmatched Credit Scores (20-23 year olds)



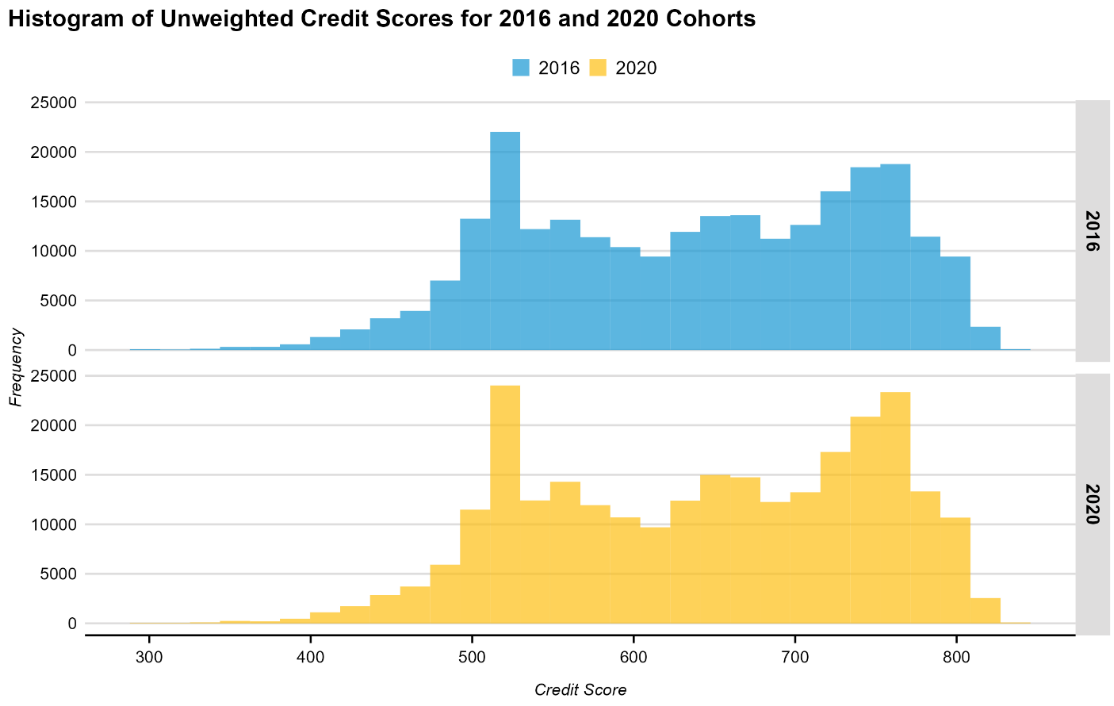


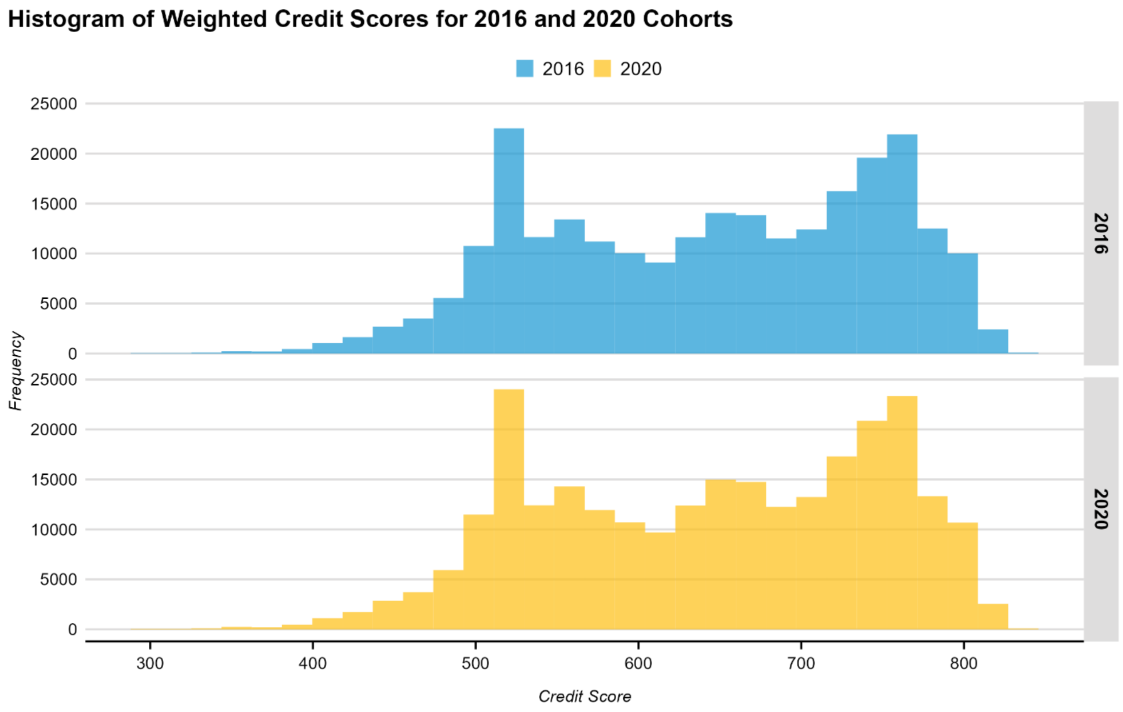
Matched and Unmatched Credit Scores (24-26 year olds)





Matched and Unmatched Credit Scores (27-29 year olds)





Oaxaca-Blinder Decomposition Additional Details

How the Three-fold Oaxaca-Blinder Decomposition Works

- First, I estimate two linear equations (one for each group of interest– majority White communities and communities of color) for the outcome of interest (young adults' credit scores) based on a group of predictors (e.g., income, education, employment, homeownership).

- Then, I conduct the decomposition, where:

  - Group differences in predictors are weighted by coefficients (from stage 1) from group 2 (communities of color) to get the endowment effect – or the expected change in young adults' credit scores (mean outcome) if group 2 had group 1's (majority White communities) predictor levels.

  - Group differences in coefficients are also weighted by group 2's predictor levels to model the expected change in group 2's (communities of color) average credit score (mean outcome) if group 2 had group 1's coefficients (or returns).

  - Group differences in predictors are weighted by group differences in coefficients capture the simultaneous differences in endowments and coefficients between each group.

Oaxaca-Blinder Decomposition Interpretation

Variable in Results Table	What It Captures
Difference in Means	Difference in means between group 1 (reference group) and group 2. In this analysis, the reference group is young adults living in majority White communities.
Endowments	Portion of the mean difference that is explained by differences in the level of observable characteristics in group 1 (reference group).
Coefficients	Portion of the mean difference explained by both: • differences in the returns to endowments of group 1 relative to group 2 (or said another way—the differences in the predicted outcome if group 1 had the regression coefficients of group 2) and • due to unobservable factors and their returns (see constant below– which directly estimates this) This reflects part of the portion of the difference in means left unexplained (the other part is the interaction effect), as differences to returns in endowments could stem from discrimination.
_cons (listed under coefficients in Appendix Tables E.1, E.2, and E.3)	Portion of the coefficient effect that is unexplained by factors included in the model -- either omitted variables or discrimination-- and their returns.
Interaction	"Interaction due to simultaneous effect of differences in endowments and coefficients" (Rahimi & Hashemi Nazari, 2021). "The interaction term indicates the (incremental) portion of the gap that occurs when both the endowments and coefficients change simultaneously; or, alternatively, the portion of the gap that remains after controlling for the endowment and coefficient portions (i.e. after controlling for the all-else-equal terms: the endowment contribution while holding the respective coefficients constant, and vice versa)." The endowment effect is really the baseline endowment effect (and the coefficient effect is the baseline coefficient effect), while the interaction effect reflects the "incremental change from group B baseline endowment effect if group B's coefficients as well as its endowments changed to match group A" (and same for coefficients).

Two-Fold vs. Three-Fold Oaxaca-Blinder Decomposition

Why Use the Three-Fold Decomposition?

- When the interaction effect explains a substantial portion of the mean difference—which is the case in this study-- using the three-fold method can help provide a clearer picture of the influences of endowments and coefficients instead of two-fold; even though it can add complexity to interpretation
- “The threefold decomposition provides a more consistent interpretation with respect to the reference group, with both the endowment and coefficient terms stating, respectively, how the reference group mean outcome would change if it had the mean characteristics or coefficients of the non-reference group. The same consistency in interpretation, however, does not happen with twofold decomposition, with the explained and unexplained portions not using the same reference group with which to weight the terms” (Etezady et al., 2020).
- In the two-fold decomposition, there is also little guidance on the appropriate reference group (e.g., discriminatory or non-discriminatory, benchmark or group values, etc.).

Regression Specification: Phase 1 Oaxaca-Blinder

$$W_{1izt} = \delta_{1t} + \beta_{1t} X_{1zt} + \phi_{1izt}$$

$$W_{2izt} = \delta_{2t} + \beta_{2t} X_{2zt} + \phi_{2izt}$$

where $\mathrm{W}_{1\mathrm{izt}}$ and $\mathrm{W}_{2\mathrm{izt}}$ are the credit score of young adult i in ZCTA z in group 1 and 2 at time t (February 2020), δ_{1t} and δ_{2t} are constants, $\mathrm{X}_{1\mathrm{zt}}$ and $\mathrm{X}_{2\mathrm{zt}}$ are vectors of correlates of credit health (including median income, educational attainment, employment status, and homeownership) *measured at the ZCTA level*, $\beta_{1\mathrm{t}}$ and $\beta_{2\mathrm{t}}$ are vectors of regression coefficients for the correlates of credit health. These coefficients are assumed to vary by group but not by time. $\phi_{1\mathrm{izt}}$ and $\phi_{2\mathrm{izt}}$ are the error terms.

Regression Specification: Phase 2 Oaxaca-Blinder (3-Fold)

$$\Delta\overline{W} = \sum_{i=1}^{k} \beta_{1t}\,(\bar{X}_{1t} - \bar{X}_{2t}) + \sum_{i=1}^{k} \bar{X}_{1t}\,(\beta_{1t} - \beta_{2t}) - \sum_{i=1}^{k} (\bar{X}_{1t} - \bar{X}_{2t})\,(\beta_{1t} - \beta_{2t})$$

Here, $\Delta\overline{W}$ reflects the difference in mean credit scores between group 1 (young adults living in majority White communities) and group 2 (young adults living in communities of color—majority Black, Hispanic, and Native American communities), *from the perspective of group 1*. Here, the entire decomposition is done from the perspective of group 1—and importantly, results will depend on the choice of reference group when conducting the decomposition. Superscripts o and 2 denote which group the term refers to, i denotes an individual consumer, $\bar{X}$ refers to averages of the covariates and β reflects coefficients estimated in Equation 3.2. $\sum_{i=1}^{k} \beta_{1t}\,(\bar{X}_{1t} - \bar{X}_{2t})$ captures the portion of the difference in mean credit scores explained by differences in the average of covariates included in the decomposition between the two groups, where covariates are measured at the *community-level* and include median income, educational attainment, employment status, and homeownership). $\sum_{i=1}^{k} \bar{X}_{1t}\,(\beta_{1t} - \beta_{2t})$ captures the differential effect of these covariates (e.g., differences in returns to endowments) and "general effect of unknown factors" (Rahimi & Hashemi Nazari, 2021, pp. 11). This term is often regarded as the "unexplained" portion of the difference in means. $\sum_{i=1}^{k} (\bar{X}_{1t} - \bar{X}_{2t})\,(\beta_{1t} - \beta_{2t})$ captures the "interaction caused by the simultaneous group differences in the covariates level and their coefficients" (Rahimi & Hashemi Nazari, 2021, pp. 5).

Regression Specification: Phase 2 Oaxaca-Blinder (2-Fold)

$$\Delta\bar{W} = \boxed{\sum_{i=1}^{k} \beta_{1t} \left(\bar{X}_{1t} - \bar{X}_{2t}\right)} + \sum_{i=1}^{k} \bar{X}_{2t} \left(\beta_{1t} - \beta_{2t}\right)$$

Where $\sum_{i=1}^{k} \beta_{1t} \left(\bar{X}_{1t} - \bar{X}_{2t}\right)$reflects the differences in credit scores between young adults living in majority White communities and communities of color (separately for young adults living in majority Black, majority Hispanic, and majority Native American communities) that can be explained by community-level differences in median income, educational attainment, employment status, and homeownership, assuming that the coefficients for young adults living in majority White communities are the "ideal" or "non-discriminatory" state. The second term reflects the unexplained portions of the difference in credit scores between young adults living in majority White communities and communities of color.

Two-Fold and Three-Fold Decomposition Results for Majority-Black Communities

	Two-Fold	Three-Fold
Mean Credit Score for Majority White Communities	652.2485	652.2485
Mean Credit Score for Majority Black Communities	585.1771	585.1771
Difference in Means	67.07143	67.07143
Explained Portion of the Mean Difference	14.81388	
Unexplained Portion of the Mean Difference	52.25755	
Difference in Means Due to Endowments		14.81388
Difference in Means Due to Coefficients		48.14564
Difference in Means Due to Interactions		4.11191

RQ 2: Oaxaca-Blinder for Black Communities (Two Fold)

```
Blinder-Oaxaca decomposition                    Number of obs     =    524,813
                                                Model             =     linear
Group 1: majorityblack_50 = 0                   N of obs 1        =     479786
Group 2: majorityblack_50 = 1                   N of obs 2        =      45027

                                (Std. err. adjusted for 524,813 clusters in id)
```

credscore	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
overall						
group_1	652.8944	.1406834	4640.88	0.000	652.6186	653.1701
group_2	585.5673	.4549125	1287.21	0.000	584.6757	586.459
difference	67.327	.4761693	141.39	0.000	66.39373	68.26028
explained	14.80926	.1644962	90.03	0.000	14.48686	15.13167
unexplained	52.51774	.4879753	107.62	0.000	51.56133	53.47416
explained						
med_inc	2.387115	.1330291	17.94	0.000	2.126383	2.647848
share_ba	9.382373	.1131256	82.94	0.000	9.160651	9.604095
share_emp	-1.41402	.0604208	-23.40	0.000	-1.532443	-1.295598
share_mort	4.453794	.1256107	35.46	0.000	4.207601	4.699986
unexplained						
med_inc	-9.768209	1.329706	-7.35	0.000	-12.37438	-7.162034
share_ba	-.8467948	.7829299	-1.08	0.279	-2.381309	.6877196
share_emp	28.23513	3.796655	7.44	0.000	20.79382	35.67643
share_mort	2.158714	1.768392	1.22	0.222	-1.307271	5.624699
_cons	32.73891	3.868447	8.46	0.000	25.15689	40.32092

RQ 2: Oaxaca-Blinder for Black Communities (3 Fold)

```
Blinder-Oaxaca decomposition                    Number of obs    =    524,813
                                                Model            =     linear
Group 1: majorityblack_50 = 0                   N of obs 1       =     479786
Group 2: majorityblack_50 = 1                   N of obs 2       =      45027

                                 (Std. err. adjusted for 524,813 clusters in id)
```

credscore	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
overall						
group_1	652.8944	.1406834	4640.88	0.000	652.6186	653.1701
group_2	585.5673	.4549125	1287.21	0.000	584.6757	586.459
difference	67.327	.4761693	141.39	0.000	66.39373	68.26028
endowments	14.80926	.1644962	90.03	0.000	14.48686	15.13167
coefficients	48.41171	.7465765	64.84	0.000	46.94845	49.87498
interaction	4.106028	.5696304	7.21	0.000	2.989573	5.222483
endowments						
med_inc	2.387115	.1330291	17.94	0.000	2.126383	2.647848
share_ba	9.382373	.1131256	82.94	0.000	9.160651	9.604095
share_emp	-1.41402	.0604208	-23.40	0.000	-1.532443	-1.295598
share_mort	4.453794	.1256107	35.46	0.000	4.207601	4.699986
coefficients						
med_inc	-15.17182	2.065043	-7.35	0.000	-19.21923	-11.12441
share_ba	-1.361587	1.258887	-1.08	0.279	-3.828959	1.105786
share_emp	29.7171	3.99589	7.44	0.000	21.8853	37.5489
share_mort	2.489114	2.03905	1.22	0.222	-1.50735	6.485578
_cons	32.73891	3.868447	8.46	0.000	25.15689	40.32092
interaction						
med_inc	5.403615	.7358677	7.34	0.000	3.961341	6.845889
share_ba	.514792	.4759759	1.08	0.279	-.4181037	1.447688
share_emp	-1.481979	.200156	-7.40	0.000	-1.874277	-1.08968
share_mort	-.3304004	.2706758	-1.22	0.222	-.8609152	.2001144

Imputation Details for ACS Data Used in Oaxaca-Blinder Decomposition

Imputed Values for ZCTAs

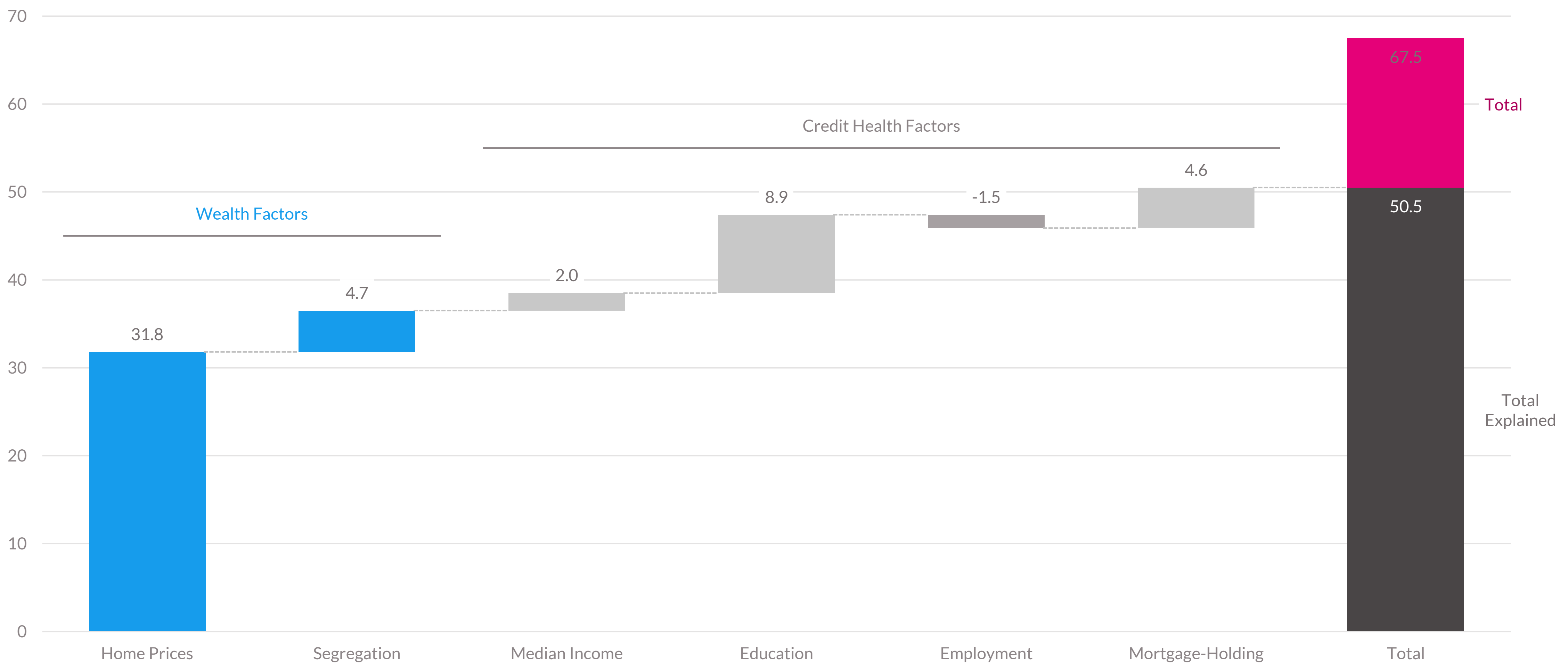
Variable	Age Range	Share of ZCTAs with Non-Missing Data	Number of ZCTAs Missing	Mean Used in Imputation (of all ZCTAs)
Bachelor’s Degree	18-24	92.5	2,453	9.8 percent
Bachelor’s Degree	25-34	94.5	1,799	26.6 percent
Employment Status	20-24	90.5	3,131	76.7 percent
Employment Status	25-29	91.2	2,891	81.1 percent
Median Income	15-24	40.1	19,828	$42,123
Median Income	25-44	82.2	5,875	$70,682

Observations Impacted by Imputation

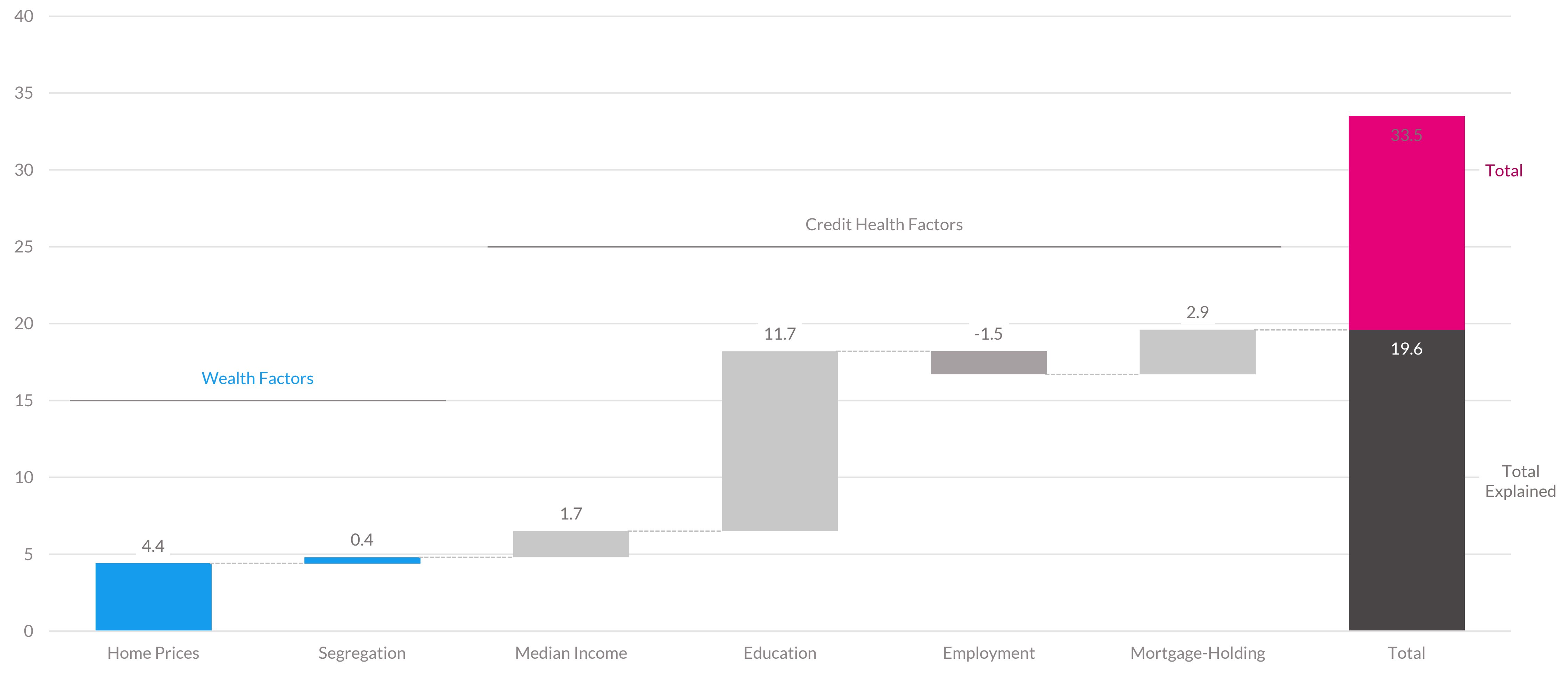
Variable	Share of Young Adults (20-29) with Missing Data	Number of Observations Missing
Bachelor's Degree	0.09 percent	730
Employment Status	0.16 percent	1,226
Mortgage Holding	0.59 percent	4,616
Median Income	9.52 percent	74,414

Waterfall Oaxaca-Blinder Plots

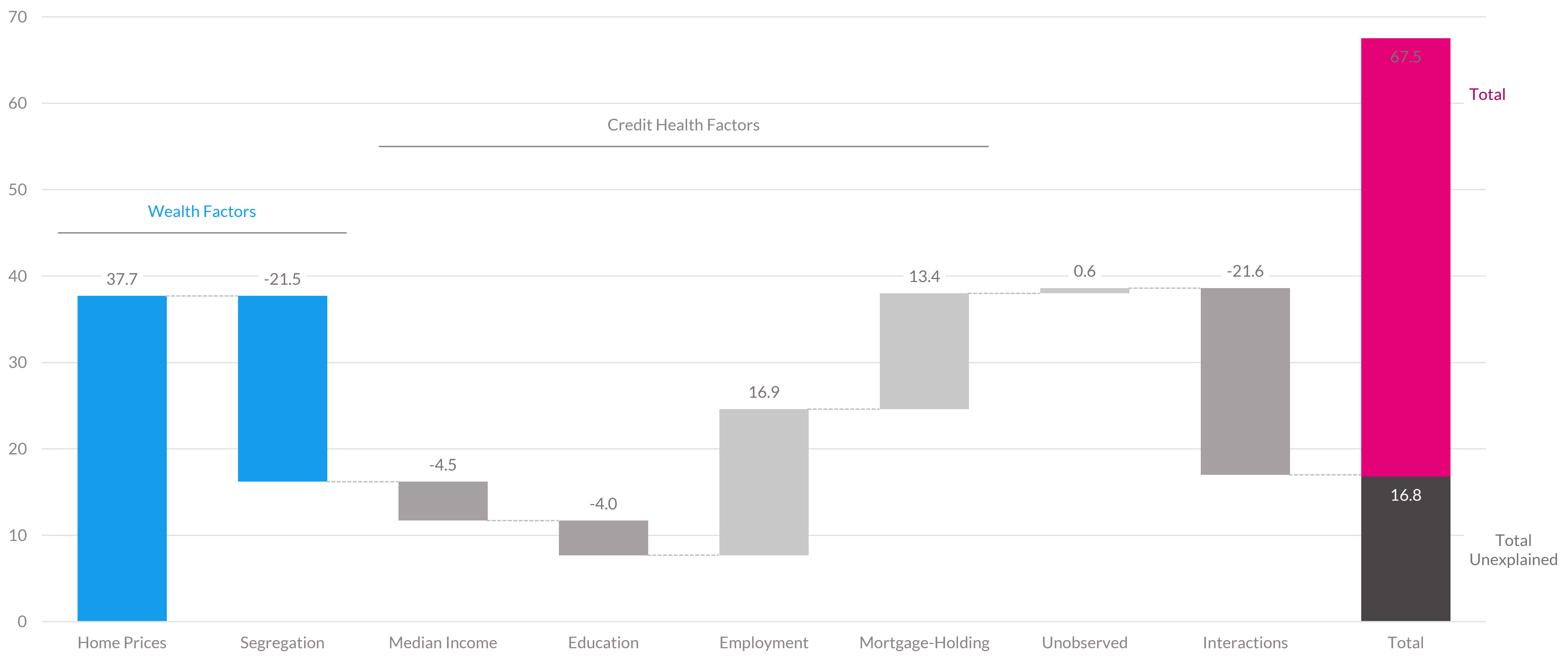
Waterfall Chart for Endowments for Majority Black



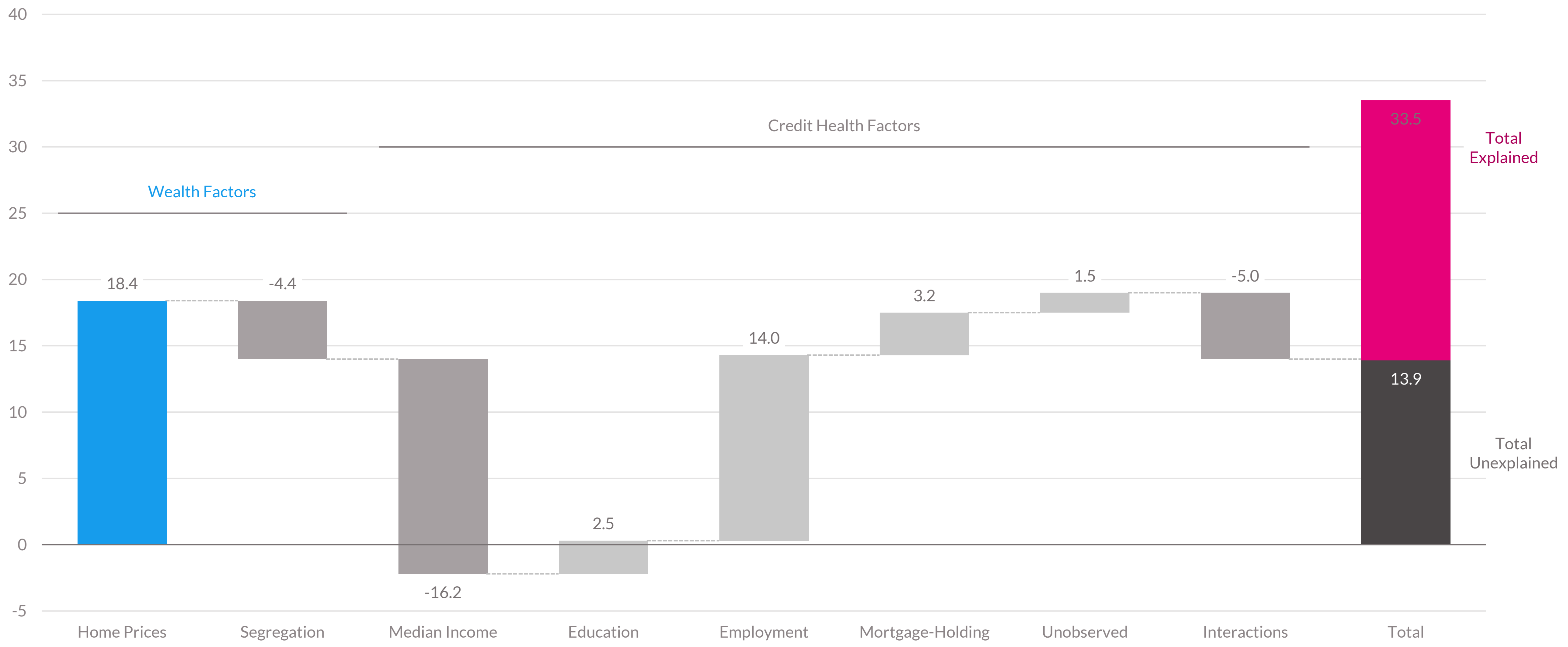
Waterfall Chart for Endowments for Majority Hispanic



Waterfall Chart for Returns for Majority Black



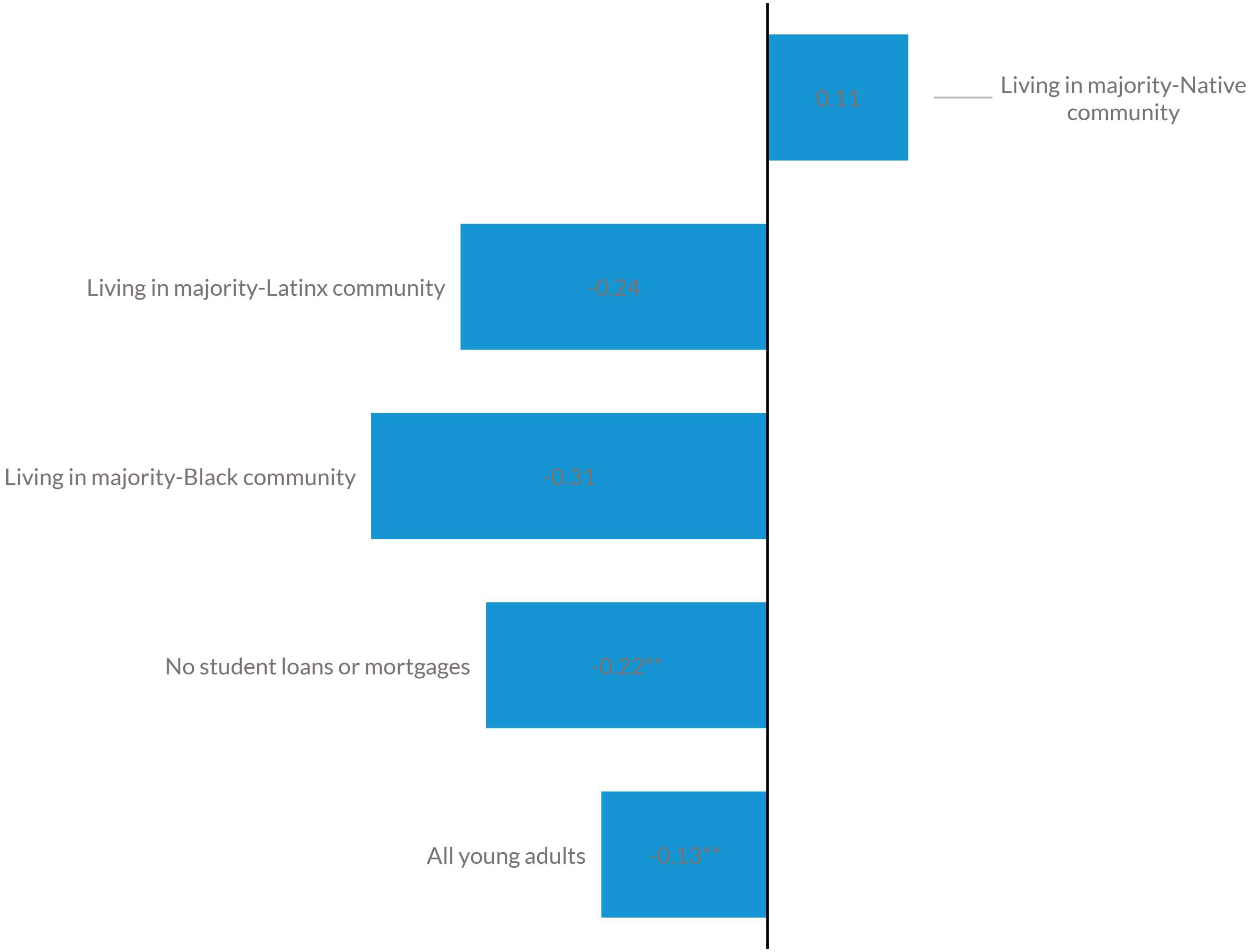
Waterfall Chart for Returns for Majority Hispanic



Additional Policy Impact Results

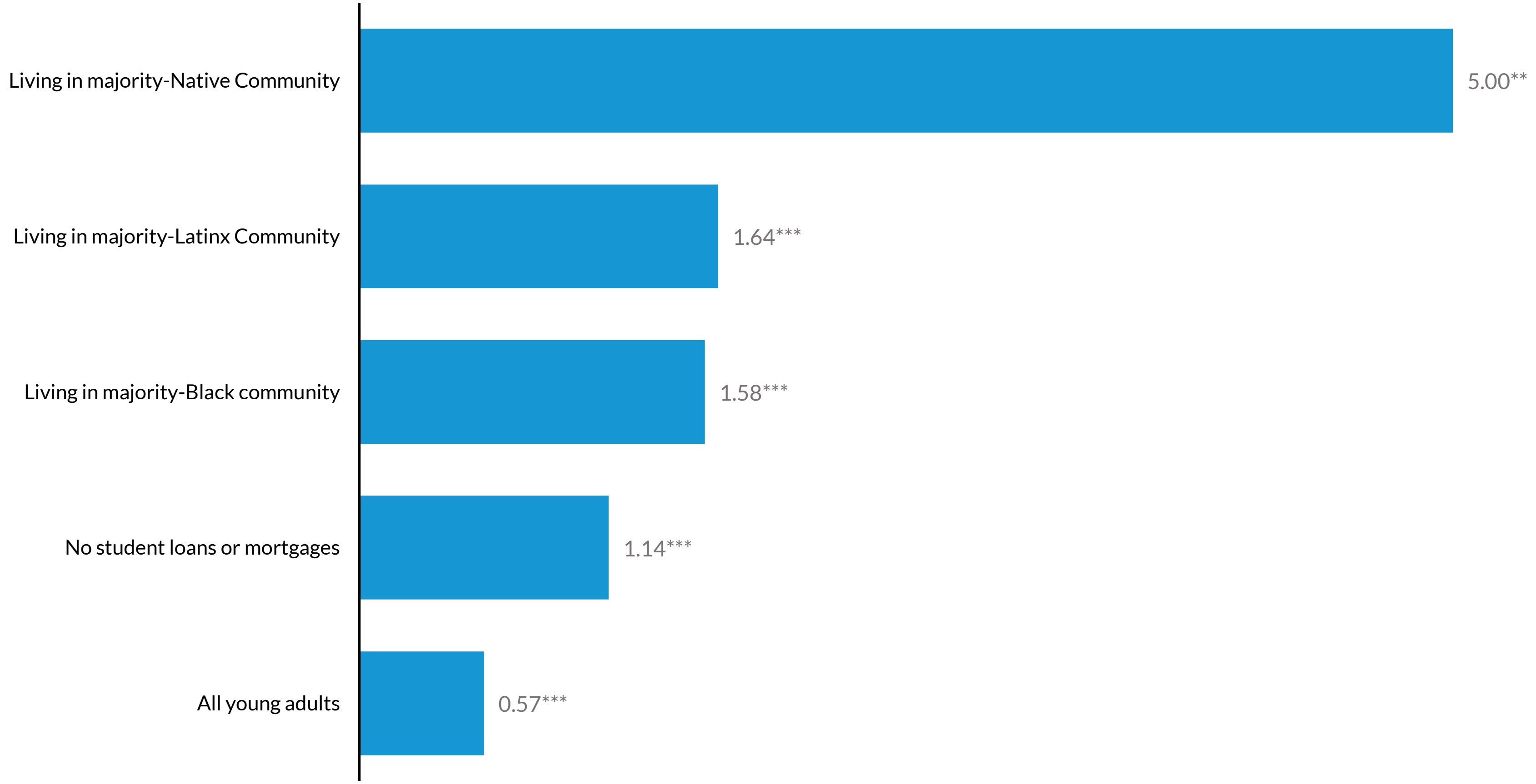
Longer Extended UI Programs (20 Week) Decreased Young Adults' Delinquencies

Percentage point changes in the share of young adults (ages 20 to 29) with a 30+ day late credit card bill after implementation of state-level 20-week extended benefits UI programs, across different groups



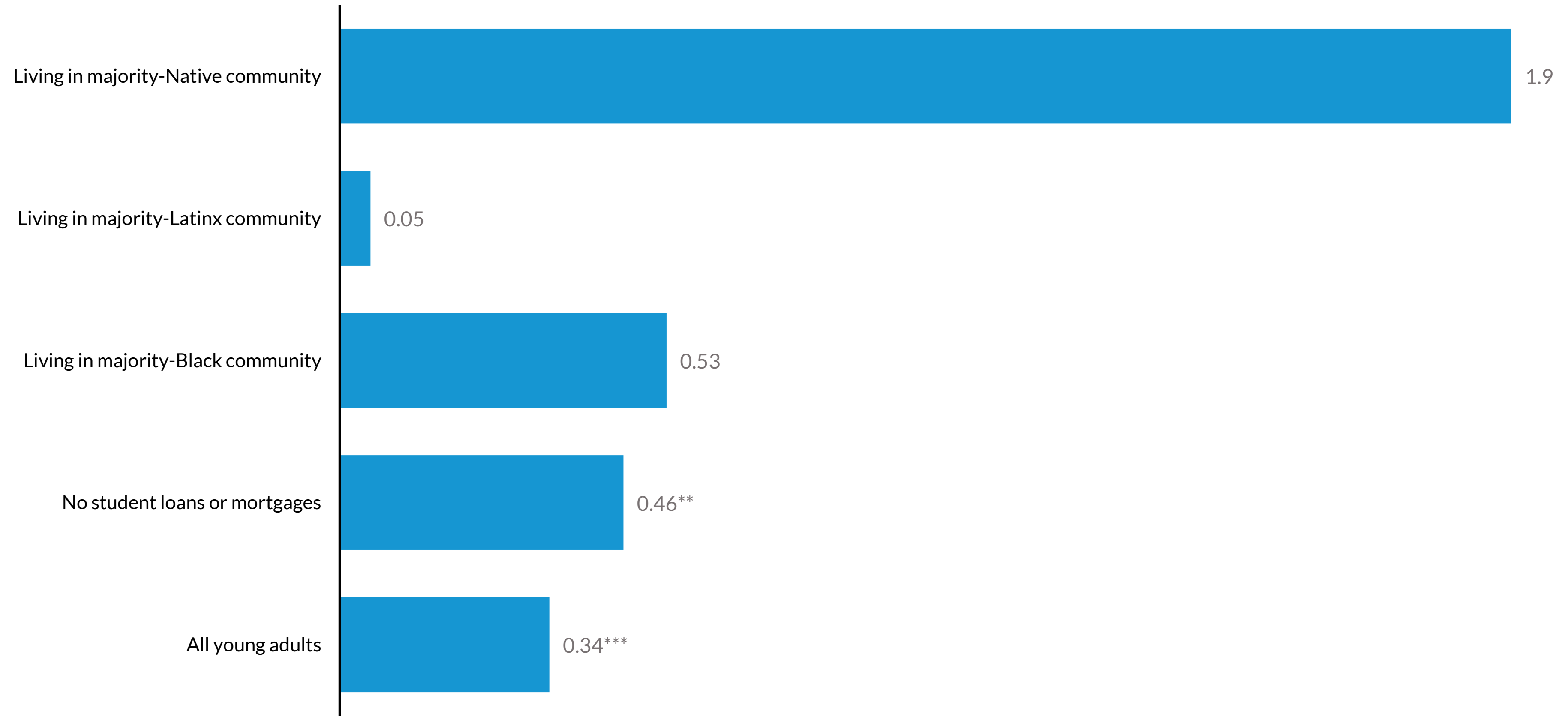
Utility Shutoff Moratoria Marginally Increased Young Adults’ Credit Scores

Changes in young adults’ (ages 20 to 29) average credit scores (in points) after implementation of state-level utility shutoff moratoria, across different groups



Longer Extended UI Programs (20 Week) Marginally Increased Young Adults' Credit Scores

Changes in young adults' (ages 20 to 29) average credit scores (in points) after implementation of state-level 20-week extended benefits UI programs, across different groups



Extended UI Programs (13 Week) May Marginally Improve Credit Scores of Young Adults Without Student Loans or Mortgages

Changes in young adults' (ages 20 to 29) average credit scores (in points) after implementation of state-level 13-week extended benefits UI programs, across different groups