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

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This is a draft paper, please do not share without the author's consent. The author welcomes feedback on this working paper. Please send all inquiries to kmartinchek@urban.org.

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Abstract

A deep body of literature suggests that young adults who experience a recession may experience long-term declines in their employment and earnings potential that undermine their ability to establish financial stability. Such challenges may especially be relevant for young adults of color and young adults living in communities of color, as prior research has found that macroeconomic downturns may worsen longstanding, structural disparities in wealth and financial well-being along racial lines. Given such challenges, many states have implemented emergency measures in the aftermath of the pandemic recession, such as more generous public supports and consumer protection policies to protect the most disadvantaged.

Using 18 waves of credit data on 806,511 young adults ages 20-29 from February 2020 to August 2023, I answer four research questions: (1) How have community-level racial disparities in young adults' financial well-being changed between 2020 and 2023?, (2) What are the community-level factors associated with these disparities in young adults' credit scores; (3) Did young adults fare better or worse during the pandemic period compared with similar young adults living in less economically volatile times (e.g., 2016-2019)?, and (4) To what extent have state policies (including extended unemployment insurance programs and utility shutoff moratoria) protected young adults or exacerbated pre-COVID inequities in credit health?. I use descriptive regression analysis, Oaxaca-Blinder decompositions, exact matching, and two-way fixed effect (TWFE) difference-in-difference models to answer these animating questions. I test the robustness of TWFE estimates on subsamples of young adults (a) living in communities of color and (b) without student loans at baseline and also use policy discontinuities at state borders to estimate policy impacts similar to work by Dube, Lester, and Reich (2010) and Schmidt, Shore-Sheppard and Watson (2020).

I find that young adults living in communities of color experienced relative improvements in their credit health early in the pandemic that show signs of reversing by August 2023, signaling worsening racial inequities three years after the pandemic recession ended. Such community-level racial disparities in credit are attributable to differences in community-level factors associated with credit health as well as community-level differences in wealth-building opportunities—although some of these disparities remain unexplained due to differences in

returns to these factors across communities of color and majority white communities. Further, despite elevated levels of economic volatility between 2020 and 2023, young adults ages 20-29 see sharper gains in credit health compared with similar young adults in 2016, with the largest relative gains occurring between 2020 and 2021 suggesting that in the early pandemic, young adults may have experienced a buffering effect against some of the adverse consequences of the pandemic recession. In examining the impact of state-level policies on utility shutoff moratoria and extended unemployment insurance benefits, I find that they likely contributed to protecting the most vulnerable populations during this time, helping to marginally improve young adults' credit scores and decrease delinquencies. Despite these effects, young adults in 2023 may be experiencing elevated levels of financial distress and greater challenges staying current on bills, which could signal the need for additional policy action to help young adults build and preserve financial stability moving forward.

Introduction

A deep body of literature suggests that young adults who experience a recession may experience long-term declines on their employment and earnings potential that undermines their ability to establish financial stability (Rinz 2019; Gould & Kassa 2020; Stevenson 2020; Rothstein 2021; Kahn 2006). Such challenges may especially be relevant for young adults living in communities of color, as prior research has found that macroeconomic downturns may worsen longstanding, structural disparities in wealth and financial well-being (Baradaran 2017). While earnings from gainful employment are one piece of young adults' balance sheets, many also use credit and debt to meet their financial needs, especially during macroeconomic shocks and their aftermath (Martinchek et al. 2022). Using debt and credit to manage macroeconomic shocks and recessions could potentially adversely affect young adults' long-term financial stability if they take on high debt burdens, struggle to pay existing financial obligations, and experience declines in their creditworthiness. During 2020, high levels of unemployment and GDP losses a short but extraordinarily deep recession that raised the question of how young adults would fare in the aftermath (Center for Budget and Policy Priorities 2023a; Center for Budget and Policy Priorities 2023b). This concern was especially pronounced for young adults living in communities of color, who were exposed to higher levels of job loss and health impacts associated with the pandemic, which would worsen existing racial disparities. At the same time, policymakers implemented substantial expansions of safety net benefits and consumer policy protections that may have served to help young adults weather the worst effects of the recession and remain financially stable.

Using novel high-frequency data on the credit records of 806,511 young adults ages 20-29, this study investigates issues at the intersection of racial equity, macroeconomic shocks, and use of debt and credit among young adults to better understand how to help young adults cope with and respond to recessions. To do this, I evaluate whether young adults living in majority-Black, majority-Native or majority-Latinx communities are less likely to meet their financial obligations during the crisis.[1] Although recent studies have documented nationwide changes in

[1] In this paper, I use the term Latinx to refer to residents of communities that reported Hispanic ethnicity across racial identities in a gender-inclusive way. Hispanic is the term used by government agencies when collecting data about populations with Latinx ethnic identities but can be associated with colonialism and can exclude populations

credit health outcomes during the pandemic (Andre et al 2024), to my knowledge this is the first study to examine changes in credit and debt for young adults specifically, with breakdowns for different communities during the pandemic. In this study and working paper, I answer the following research questions:

- RQ1: How have community-level racial disparities in young adults' (ages 20-29) credit and debt changed in the wake of the COVID-19 pandemic?
- RQ2: To what extent do community-level factors associated with credit health and differences in community-level wealth-building opportunities explain community-level racial disparities in young adults' credit scores?
- RQ3: How have the credit health trajectories of young adults (ages 20-23, 24-26, and 27-29) from 2020 to 2023 compared with similar young adults in less economically volatile times (2016-2019)?
- RQ4: 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?

Ultimately, this study contributes to literature aimed at understanding how to support young adults in building resilience to economic shocks, which is summarized below.

Young Adulthood and the Challenges of Building Financial Security during Recessions

Compared with older adults, young adults often face challenges in responding to financial emergencies because of lower levels of resources, including savings, assets and investments, family financial support, insurance, and access to credit (Cramer 2020; Killewald and Bryan 2018; Perry and Donoghoe 2023; Martinchek forthcoming). This lack of financial resilience is underscored by their average lower levels of savings, assets, and access to credit compared with older adults, indicating they may face steeper challenges in remaining financially solvent during tough economic times (Martinchek forthcoming).

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that do not trace their ancestry to Spain. Throughout this paper, I use the term Native to refer to populations and communities that reported they had Native American or American Indian ancestry. In doing so, it is important to recognize that Native Americans are not monolithic, and that this term—which colonizers created—will not resonate with all tribal citizens and communities. I acknowledge these may not be the preferred identifiers and remain committed to employing inclusive language whenever possible.

Young adulthood is when consumers commonly accumulate more debt and save less, prioritizing investments in human capital and assets for future economic mobility (Ando and Modigliani 1963; Modigliani and Parkin 1975). However, taking on significant debt with limited assets can present challenges in repaying debt that can contribute to short-term financial distress or delayed investments in critical financial milestones (Cramer 2020; Friedline and Freeman 2016; Henry 2017; Martinchek forthcoming).[1]

Previous research indicates that young adults, in particular, may encounter difficulties in recovering and establishing financial security during recessions. Studies on postrecession employment and earnings trajectories reveal that those entering the labor market during economic downtowns experience lower employment and earnings even a decade after the recession has concluded (Ellwood 1982; Kahn 2006; Rinz 2019; Rothstein 2021; Wachter 2020).

Structural Racism and Persistent Disparities in Community-Level Financial Well-Being

Research demonstrates significant and enduring disparities in credit health rooted in race and ethnicity. These disparities stem from race-based and race-neutral policies that have limited wealth-building opportunities and access to credit at the community level (Baradaran 2017; Furtado, Verdeflor, and Waidmann 2023; Kijakazi et al. 2019; Rothstein 2017).[2]

In the mid-20th century, the discriminatory practice of redlining classified communities as “hazardous” investments based on their changing racial and ethnic compositions, leading to the denial of mortgage applications from residents in those designated areas (Faber 2019; Mitchell and Franco 2018). Although no longer in practice, redlining has left a lasting impact by fostering and perpetuating homeownership gaps between white and Black households, racial disparities in housing price appreciation and wealth-building returns, and entrenched residential segregation (Aaronson, Hartley, and Mazumde 2021; Baradaran 2017; Faber 2019; Markley et al. 2020; Mitchell and Franco 2018; Rothstein 2017).

[2] Beyond shaping community-level opportunities and resources, these policies have also shaped young adults’ individual-level outcomes (Baradaran 2017; Rothstein 2017). Young adults of color, for instance, hold less wealth and savings than their white peers and are more likely to have a negative net worth (Cramer 2020; Killewald and Bryan 2018; Perry and Donoghoe 2023). This dynamic is important to note, but in this analysis, I focus on community-level racial disparities.

Other policies, including the discretionary application of G.I. Bill benefits, predatory practices in subprime lending pre-2008, and geographical targeting of high-cost and traditional credit based on community demographics, have further exacerbated racial disparities in wealth and credit (Baradaran 2017; Dymski 2009; Gale 2021; Goodstein and Rhine 2017; Katznelson 2005; Markley et al. 2020; Martinchek forthcoming; McKenna 2008; Rothstein 2017; Taylor 2019; Wyley et al. 2009).

Importantly, the cumulative impact of these policies has shaped the geography of opportunity *at the community level*. This has led to racial residential segregation, clustering people of similar races together, creating distinct groups with disparate access to affordable credit, wealth-building opportunities, and economic mobility prospects (Acs et al. 2017; Baradaran 2017; Rothstein 2017; Turner et al. 2022). Such economic segregation within racially segregated communities results in lower quality of life and wealth for residents (Acs et al. 2017). Ultimately, a long-standing history of policies and practices has left communities of color and the young adults residing within them with cumulative disadvantages and fewer supports for mobility and recovery.

Dynamic Risks to Racial Equity: Examples from the Great Recession

Communities' disparities in wealth and credit are not static and face the potential of widening during economic shocks, posing a dynamic threat to advancing racial equity in financial well-being (Martinchek forthcoming; Neal and McCargo 2020).

During the Great Recession, existing racial disparities in homeownership and overall wealth were exacerbated during the recovery, despite policies like the Troubled Asset Relief Program and Neighborhood Stabilization Program aimed at preventing foreclosures (Neal and McCargo 2020). Ultimately, these initiatives did not address structural differences in vulnerability to foreclosure between communities of color and majority-white communities entrenched through targeted subprime lending, redlining, and racialized lending practices (Baradaran 2017; Rothstein 2017).

As a result, communities of color faced concentrated foreclosures and vacancies and higher rates of negative home equity, and they experienced a slower and less-pronounced recovery (Immergluck 2016; Raymond 2018; Reid 2021; Rothstein 2017; Sharp, Whitehead, and Hall 2020; Taylor 2019). Black, Latinx, and Native families were more likely to lose wealth and accumulate high debt during the aftermath of the Great Recession—leaving them on less-stable financial footing over a longer period than their white peers (Pfeffer, Danziger, and Schoeni 2013; Zhang and Feng 2017).

Ultimately, the persistent and pronounced disparities in community-level risks and assets between communities of color and majority-white communities may render residents of communities of color more vulnerable during economic downturns, causing them to fall further behind their peers in more well-resourced communities (Neal and McCargo 2020). Current research could extend its focus to better understand how dynamic risks evolve during recessions, particularly concerning debt and credit outcomes, which are relatively understudied compared with housing and employment outcomes.

Policies as Buffers

While recessions pose threats to young adults' financial security and can exacerbate racial inequities in wealth and credit, policies can help people navigate economic shocks and narrow existing inequities.

Recent research examining pandemic-era investments in social insurance and safety net programs suggests that such investments may have contributed to reducing child and household poverty, food insecurity, and material hardship amid heightened economic volatility (Karp man and Acs 2020; Karpman et al. 2021, 2022; Wheaton and Kwon 2022). Further, the Federal Reserve's findings show a narrowing racial wealth gap between 2019 and 2022 because of increased asset investments among families of color. However, income expectations and stability for these families worsened, leading to more pessimistic views of their financial futures.

Studies investigating state-level policies reveal the positive impact of utility shutoff and eviction moratoria in reducing use of nonbank loans such as payday loans and lowering delinquencies on auto loans and credit cards during freezes (Andre et al., 2024; Andre et al., 2023). These policies potentially increase individuals' resources to respond to economic shocks or minimize their impact (Martinchek forthcoming).

This Study's Contribution

This study builds on these bodies of prior literature to: (1) quantify trends in young adults' financial well-being (as measured by credit health) during a unprecedented macroeconomic shock, (2) decompose well-documented community-level racial disparities in credit health into contributing community-level factors, (3) track how the pandemic cohort of young adults fared over a three-year period compared with similar young adults who experienced a less economically volatile period, and (4) explore the impact of state-level consumer protection and safety net policies on the financial well-being of young adults.

Data

I drew on several data sources to measure young adults' credit outcomes, capture community-level racial demographics, represent state-level policies, and control for COVID-19 cases and deaths, economic volatility, and pandemic-related business closures.

The primary data source for this study is Urban Institute longitudinal credit bureau data from August 2019 to August 2023. These data consist of a random 2 percent sample of deidentified consumers from a major credit bureau (about 5.5 million consumers). The credit bureau data contain an array of information on consumer credit profiles as well as geographic identifiers at the zip code–level and ages for all adults with a credit file. All records were stripped of personally identifiable information. To keep the sample representative at the national level, the consumer panel is refreshed at each data pull.

Notably, the data do not include details on 11 percent of US adults with no credit record, with people of color and young adults disproportionately represented among these credit invisibles nor do these data contain details on individual consumers' race or ethnicity (Brevoort, Grimm, and Kambara 2015).

In my analysis, I restrict the sample to the 806,511 consumers between ages 20 to 29 observed in the credit bureau data in February 2020 (or August 2016 for the cohort-level analysis).[3] I classify consumers based on their credit score and ZIP Code of residence in these baseline periods when conducting any subgroup analysis.

[3] Because I only keep consumers who are observed in February 2020, I assess the risk of experimental mortality in later time periods. From February 2020 to August 2023, 8.44 percent of the initial sample between ages 20-29 attrits. Consumers who disappear from the sample by August 2023 are slightly more likely to be subprime in February 2020 and are significantly less likely to have a credit card. Among consumers who disappear from the sample, 43.8 percent have subprime credit scores in February 2020 and 71.7 percent do not have credit cards in February 2020. Consumers who remain in the panel in August 2023 are more likely to have credit cards and prime scores in February 2020, with 32.6 percent having subprime credit and 42.4 not having credit cards in February

Outcomes

The two primary outcomes for analysis are drawn from the credit bureau data panel:

- **Credit scores** reflect consumers' ability to repay loans, with subprime scores below 600 indicating potential barriers to credit access and higher associated costs (Elliott and Lowitz 2018). These scores are influenced by consumers' payment histories, the share of available credit used, the length of credit history, credit product mix, and recent credit inquiries. I used the average VantageScore (from 300 to 850) of consumers with credit bureau records as an outcome in this study.[4]
- **Credit card delinquencies** can indicate whether consumers are experiencing challenges making ends meet and meeting existing financial obligations. Unpaid credit card bills can undermine young adults' creditworthiness, signaling distress. I measure whether consumers with at least one open credit card are 30 days or more past due on payments. This early measure captures whether consumers have at least one missed credit card bill, which can lower consumers' credit scores marginally. However, this measure also captures later stages of delinquencies, involving longer periods of nonpayment, leading to substantial drops in overall credit scores, high fees, and interest that can be challenging to repay, along with the risk of accounts moving into collections.

2020. These differences in credit card holding and credit tier between young adults who remain in the sample and those that attrit are statistically significant at the $p<0.01$ level using a two-tailed t-test.

[4] VantageScore is one type of credit-scoring algorithm that uses slightly different criteria than FICO to determine scores. FICO and VantageScore vary in how long it takes for consumers to generate a scorable file (VantageScore requires any open account while FICO requires an account older than six months); the importance of different factors in scoring (VantageScore prioritizes payment history, credit depth, credit utilization, recency of credit, current balances, and available credit presence, while FICO scores are based on payment history, amounts owned, credit history length, presence of new credit, and mix of credit types); and the impact of credit inquiries on scores, and the values of their scores—or which scores are considered good (over 600 for VantageScore is prime, while over 660 is prime for FICO). Further, FICO is more often used by lenders to decide if consumers are approved for loans, including mortgages—although these scores vary among each of the three credit bureaus. Additionally, FICO provides industry-specific scores for auto lenders and credit card issuers so are often used in those industries. I used VantageScores in this analysis as FICO scores were not available in the data. See Johnson (2023) for additional details. It is also important to note that during this time certain types of loan delinquencies were not penalized on consumers' credit reports because of active forbearance policies, so the content of credit scores in terms of evaluating consumers' creditworthiness differs from other periods where such policies are not in effect.

ACS Data

To disaggregate results across racial demographics, I used Zip Code Tabulation Area (ZCTA)–level data on racial and ethnic demographics from the five-year American Community Survey (ACS) from 2015 to 2019. As credit bureau data lack individual consumers' race and ethnicity details, I used these data to categorize communities (or ZCTAs) into majority-Black, majority-Latinx, majority-Native, and majority-white communities to examine heterogenous effects between young adults living in different communities.

To create this classification, I first merged ACS data on community-level (ZCTA) race and ethnicity with credit bureau data using consumers' zip codes of residence in February 2020. I then used ACS population data to categorize communities, following similar approaches taken in Martinchek and colleagues' dataset (2021) and Andre et al. (2024, 2023).[5] Majority communities are defined at a 50 percent threshold where 50 percent or more of the ZCTA's residents identify with the racial or ethnic group of interest in the 2015–19 ACS.[6]

Although this approach is imperfect for examining individual-level credit and debt outcomes, it is well-suited to investigate community-level disparities that are central to this study and aligns with a substantial body of scholarship emphasizing the role of residential segregation in shaping individual residents' financial outcomes. By adopting a community-level approach,

[5] I used the ZCTA of residence of consumers in February 2020 to identify consumers who lived in majority-Black, majority-Latinx, majority-Native, and majority-white communities to account for potential endogeneity of migration decisions in response to state-level policies, as is done in Andre et al. (2024, 2023). Additionally, in this paper, I used community-level race and ethnicity to explore heterogenous trends in young adults' credit and debt and policy impacts. Large bodies of research document the role of residential segregation in shaping residents' outcomes—particularly financial outcomes—which supports the value of an analysis that explores how residents' credit health can be shaped by the communities in which they live (Acs et al. 2017; Baradaran 2017; Rothstein 2017). As administrative credit bureau records do not contain details on individual consumers' race and ethnicity, other research efforts have tried to predict consumers' race and ethnicity using ancillary data, and this is an area of current research inquiry and innovation. See Brown et al. 2021; CFPB 2014; and RAND 2023, for a discussion.

[6] It is possible that results could be sensitive to the selected cutoff for the share of residents who identify as a particular race or ethnicity, or my definition of "majority" communities. In this study, I largely use a 50 percent cutoff, where communities are categorized as majority if more than 50 percent of ZCTA residents in the 5-year ACS identify as members of a particular race or ethnicity. 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 RQ1 and RQ2 across three different community demographic compositions: 30 percent, 50 percent, and 80 percent of residents who identify as Black, Latinx, or Native. 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, Latinx, and Native communities; with results that generally became more striking as communities became more racially and ethnically diverse (in terms of the magnitude of the community-level racial disparity in credit and debt outcomes at the beginning and throughout the pandemic for young adults living in these communities). For space, these results are not shown.

the study explores how racially clustered areas may limit young adults' opportunities to build and preserve strong credit profiles (Baradaran 2027; Furtado, Verdeflor, and Waidmann 2023; Rothstein 2017). This community-level approach shifts focus "away from an individual's race as associated with disparities and toward systems and structures as drivers of disparities" (Balu et al. 2023, p. 6).[7] Consequently, this study examines the outcomes of *young adults living within various communities*, reflecting differences in credit and debt outcomes at the community (or ZCTA) level.

I also use ACS data to capture community-level factors that could influence consumer credit scores in answering RQ2. I use ZCTA-level data from the ACS on the following and merge it onto the credit bureau data based on consumer age and ZCTA of residence in February 2020: (1) *educational attainment*: the share of ZCTA residents with a bachelor's degree or higher for adults ages 18-24 and 25-34; (2) *median income*: median income over the past 12 months for adults ages 15-24 and 25-44 in the ZCTA; (3) *employment status*: the share of ZCTA residents with employment for adults ages 20-24 and 24-29; and (4) *mortgage-holding*: the share of ZCTA residents with a mortgage, by householder age, for adults ages 15-34. To address missingness in the ACS data before conducting the decomposition, 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.[8] I use imputation to ensure all ZCTAs have values for all variables, as conducting the Oaxaca-Blinder decomposition used in RQ2's analysis requires complete cases with respect to the variables used in the decomposition.

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

[7] Using community-level demographics as a proxy for residential clustering by race and ethnicity offers advantages: (1) it is available at a low level of geographic aggregation—the ZCTA level; and (2) it covers both rural and urban areas, where dissimilarity indices (which are often used to measure residential segregation and clustering) are often available only in urban areas or at higher geographies (Furtado, Verdeflor, and Waidmann 2023).

[8] Relatively few ZCTAs required mean imputation in the overall sample, except for age-specific median income variables for young adults (see Table A.1 and A.2). 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.

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.

Policy Variables

To gauge policy impacts in RQ4, I relied on data detailing the timing and duration of state-level policies from two sources: (1) data on state-level utility shutoff moratoria from the National Consumer Law Center (NCLC); and (2) data on state-level UI policies from the COVID-19 US State Policy Database (CUSP).

At the same time as states implemented utility shutoff moratoria and extended UI programs, they also implemented a spectrum of policies and practices targeting consumer financial well-being. This included state-level financial assistance and consumer protections, in addition to federal interventions such as stimulus checks, enhanced unemployment benefits, and emergency increased allotments for safety net programs.

Given the large and multifaceted nature of state and federal policy innovations, capturing their effects on consumer credit health requires additional data to isolate the impact of the policies of interest. To do this, I used data on garnishment suspensions, repossession suspensions, and state-level eviction moratoria from NCLC. I also incorporated data on differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from CUSP to control for other state-level policies affecting consumer credit outcomes differentially over time across implementing and nonimplementing states.

Contextual Control Variables

Beyond considering state-level time-varying policies that could affect consumer credit health during the study period, I also addressed differences in states' COVID-19 cases and deaths, economic volatility, and pandemic-related business closures. This involved utilizing data on 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; and state-level business closures from CUSP.

Research Design and Methods

I use four methodologies to answer my key research questions of interest:

1. To explore whether community-level racial disparities in young adults’ credit health changed between 2020 and 2023, I use descriptive regressions;
2. To decompose the difference in community-level racial disparities in young adults’ credit scores, I use a three-fold Oaxaca-Blinder decomposition;
3. To assess differences in cohort-level trends in credit scores over a three-year period between young adults in 2016 and those in 2020, I use exact matching and descriptive regression analysis; and
4. To identify the effect of state-level consumer protection policies on young adults’ credit scores and credit card delinquencies, I use difference-in-difference design.

Descriptive Regression

For my first research question, I test whether the financial well-being of young adults living in communities of color changed compared with young adults living in majority-white communities during the pandemic using the following model:

$$Y_{it} = \alpha_1 Community_i + \alpha_2 Community_i \times \theta_t + \theta_t + u_{izt}$$

In this model, Y_{it} represents the credit or debt outcome of interest of young adult i in 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.[9] This specification is run

[9] I use a descriptive regression specification with main and interacted effects for community composition and period, without additional 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. However, in this model, adjusted R-squared values remain low. To test remedies for additional explanatory power, I ran

separately for each credit outcome and for young adults living in majority Black, Latinx, and Native communities.

Oaxaca-Blinder Decomposition

I use a three-fold Oaxaca-Blinder decomposition to decompose differences in young adults' average credit scores across communities into contributing factors (Rahimi & Hashemi Nazari, 2021; Etezady et al 2020).[10] [11] This analysis is conducted in two stages. First, I estimate the equation below for each group of interest (one for the group of young adults living in majority white communities and labeled group 1, and another for the group of young adults living in different communities of color (which is done separately for young adults living in majority Black and Latinx communities) and labeled group 2).[12]

$$W_{1izt} = \delta_{1t} + \beta_{1t} X_{1zt} + \phi_{1izt}$$
$$W_{2izt} = \delta_{2t} + \beta_{2t} X_{2zt} + \phi_{2izt}$$

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specifications 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. However, when adding individual fixed effects, it is not possible to answer RQ1, as initial differences across communities are absorbed in the fixed effect, so this specification does not allow for a full investigation of the research questions of interest in this paper. Given the coherence of substantive findings across different models with fixed effects, in this paper, I present the results from the specification without additional controls or fixed effects. For space, I do not present these robustness checks.

[10] The two-fold decomposition decomposes the difference in means into explained and unexplained portions, while the threefold decomposition further disaggregates contributions to the difference in means into (1) endowment effects, (2) coefficient effects, and (3) interaction effects; where the endowment effect of the threefold and two-fold decompositions are mathematically equivalent and the coefficient and interaction effects of the threefold method are considered "unexplained". 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. For instance, "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).

[11] I also conduct the analysis on non-imputed data when looking at community-level correlates of credit health, , including young adults' ZCTA-level median household incomes, employment rates, educational attainment, and mortgage-holding (see tables B.1, B.2, and B.3).

[12] Because the Mobility Metrics data does not have estimates for Native households separately, I do not present results for this racial group in the results section of this paper. I do discuss results for the ACS variable only specification of the decomposition in the appendix and in footnotes, but not in the main text.

In this model, 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 community characteristics (including income, education, employment, homeownership, housing wealth, and residential segregation) *measured at the ZCTA level*, β_{1t} and β_{2t} are vectors of regression coefficients for the these variables. These coefficients are assumed to vary by group but not by time. ϕ_{1izt} and ϕ_{2izt} are the error terms.

Then, I use these equations from stage 1 to estimate:

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

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), from the perspective of group 1. Here, the entire decomposition is done from the perspective of group 1. 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). $\sum_{i=1}^{k} (\bar{X}_{1t} - \bar{X}_{2t})\,(\beta_{1t}\ - \beta_{2t}\,)$ captures the “interaction caused by the simultaneous group differences in the covariates level and their coefficients” (Rahimi & Hashemi Nazari, 2021, pp. 5). Together, the last two terms are often regarded as the “unexplained” portion of the difference in means (see table A.7 for further details).

I run this analysis with two sets of explanatory factors: (1) community-level correlates of credit health, including young adults’ ZCTA-level median household incomes, employment rates, educational attainment, and mortgage-holding from the ACS; and (2) these factors plus measures of community-level wealth-building opportunities, including measures of residential segregation and housing wealth accumulation by race and ethnicity from Mobility Metrics.

Exact Matching and Cohort-Level Descriptive Analysis

I use a descriptive, matched cohort analysis approach to assess the extent to which young adults (ages 20-23, 24-26, and 27-29) who entered the credit market during the pandemic recession in 2020 experienced differential credit scores over a three-year period compared with similar adults who entered the credit market in non-recessionary times (2016) and whether these trends varied across community demographics.

First, 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.[13] 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). In the matching process, relatively few observations remain unmatched between the unmatched and matched samples but exact matching effectively removes baseline differences in credit scores between cohorts that could signal selection bias (see tables A.8 and A.9 for further details on matching).

After matching, I run the following model on each matched sample (and for sub-samples of young adults living in majority Black, Latinx, and Native communities) to test for statistical differences in credit score trends across each cohort (2016-2019 and 2020-2023):

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

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, two, and three 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

[13] I remove consumers who appear in both cohorts from the analysis. This removes 23,322 consumers from the 20-23 sample (4.5 percent of the sample), 87 consumers from the 24-26 sample (0.06 percent) and 58 consumers from the 27-29 sample (0.03 percent).

heteroskedastic-robust error term, which is clustered at the ZCTA level and is adjusted for the matching weights.

Difference-in-Difference

I used a staggered difference-in-difference design to gauge the impact of different state-level policies on young adults' credit health. I measured the policy impacts of two state-level policies between 2020 and 2023: (1) utility shutoff moratoria; and (2) extended UI programs (both 13- and 20-week programs).

Throughout the pandemic, states varied in their implementation, duration, and timing of these policies. I exploited these variations to measure the impact of such policies on *all* young adults while controlling for other state-level consumer protection and safety net policies, differences in COVID-19 metrics (cases, vaccinations, and deaths), economic volatility indicators (unemployment rate, home price changes), and pandemic-related business closures.

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

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.[14] $Policy_{st}$ 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

[14] 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).

programs, and an indicator for whether states had an active eviction moratorium in each period. Standard errors are clustered at the state level.[15] My preferred specification includes controls and individual consumer-level fixed effects.

These policy impacts are intent-to-treat (ITT) effects estimated for all young adults, irrespective of whether they received benefits from the policies. I explore potential treatment-on-the-treated effects (TOT) in the discussion section of this paper.

Robustness Checks to the Impact Analysis

To complement this 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:

1. 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;
2. 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
3. quantified policy impacts within a set of paired contiguous counties, comparing states that implemented policies in the period with those that did not.

First, I ran the difference-in-difference model outlined above on a subsample of consumers living in bordering counties within states that implemented utility shutoff moratoria or extended UI benefits programs and their neighboring counties within states that never implemented that policy using data from the 1991 Census Bureau Contiguous County File, following a similar approach as in Andre et al. (2024, 2023). I identified contiguous counties separately by period and policy. Contiguous counties were more likely to suffer the same health and economic shocks but differed in their policy responses.

Second, I ran the difference-in-difference model outlined above on a subsample of young adults without student loans or mortgages, who likely did not benefit from federal-level forbearances on student loans and mortgage repayment.

[15] Past work has shown that infection rates and shelter-in-place policies only explain a small portion of the variation of economic outcomes during the pandemic (Kim, Parker, and Schoar 2020), while unemployment rates and UI generosity had more significant impacts on financial outcomes (Ganong et al. 2022; Wang et al. 2020). Research also shows that moratoria on vehicle repossessions and state eviction moratoria positively affected families' credit health and financial well-being during the pandemic (Bakshi and Rose 2021).

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). 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.

Results

Community-Level Racial Disparities in Young Adults' Credit Health Between 2020 and 2023

Given the high levels of unemployment and economic volatility observed during the pandemic recession, we may expect young adults' debt and credit to worsen in the years following the recession, as young adults experience higher levels of financial distress and struggle to repay debts and meet their day-to-day financial needs simultaneously (Martinchek, 2020; Martinchek & Warren, 2020). However, at the same time, large federal investments and changes in consumer behavior (due to public health ordinances) may have provided a protective buffer against the recession's second-order effects on young adults' debt and credit (Martinchek, 2024b).

Further, I expect that longstanding disinvestment, residential segregation, and resource extraction in communities of color likely result in large, persistent disparities in credit health between young adults living in communities of color and those living in majority white communities. Evidence from prior recessions suggests that such structural vulnerabilities within communities of color may leave residents more susceptible to adverse economic effects associated with recessions (Neal & McCargo, 2020). As such, in the aftermath of the pandemic recession, we might expect that young adults living in communities of color may fall further behind those living in majority white communities (i.e., we observe that community-level racial disparities in young adults' credit and debt widen over the pandemic)—unless policies implemented provided race-conscious counter-cyclical supports to residents of these communities—*preventing* existing gaps from widening any further during the pandemic recovery (Martinchek, 2024b).

Credit Scores

Examining young adults' credit health trends throughout the pandemic, I observed a consistent improvement in credit scores for young adults living in all communities, including majority-white, majority-Black, majority-Latinx, and majority-Native communities (figure 1). However, young adults living in communities of color had worse credit scores at the beginning of the pandemic and throughout relative to peers living in majority-white communities.

In February 2020, adults living in majority-Black communities had credit scores 67.0 points lower than their peers in majority-white communities. Similarly, those living in majority-Latinx and Native communities had credit scores 33.5 and 74.8 points lower than young adults living in majority-white communities (figure 2, see table B.4 for the full regression table).

Community-level racial disparities in credit scores between young adults living in majority-white and Black communities narrowed by 5.2 points or 7.7 percent by August 2023, relative to February 2020 (figure 2, see table B.4 for the full regression table). These disparities were smallest in August 2021, with a decline of 6.6 points, relative to the beginning of the pandemic. Similarly, community-level racial disparities in credit scores between young adults living in majority-white and majority-Latinx communities showed a marginal narrowing of 0.4 points, representing a 1.1 percent decline by August 2023 (figure 2).[16]

Credit Card Delinquencies

Analyzing young adults' credit health trends during the pandemic, I observed a significant decrease in credit card delinquencies in the first year (2020) followed by an increase post-August 2021 to levels higher than before the pandemic (figure 3). While similar trends emerged across young adults living in majority-white, majority-Black, majority-Latinx, and majority-Native communities, those in communities of color consistently experienced higher credit card delinquencies from the pandemic's onset and throughout.

Notably, the escalation of credit card delinquency rates between late 2021 and 2023 was more pronounced for young adults living in majority-Black and majority-Native communities, with 1 in 5 young adults with a credit card living in majority-Black communities falling more than 30 days behind on their credit card payments by August 2023 (figure 3). In February 2020 young adults living in majority-Black communities had credit card delinquency rates 9.5 percentage points higher than peers in majority-white communities. Similarly, prepandemic credit card delinquency gaps were 4.0 percentage points for young adults living in majority-Latinx communities and 6.6 percentage points for young adults living in majority-Native communities (figure 4).

Community-level racial disparities in credit card delinquencies between young adults living in majority-white and majority-Black communities widened by 2.5 percentage points, or 26.3 percent, by August 2023 compared with the beginning of the pandemic in February 2020 (figure 4, see table B.5, for the full regression table). However, in August 2021, these disparities were 34.7 percent lower than they were at the beginning of the pandemic, a relative reduction in community-level racial disparities of 3.3 percentage points. Similarly, community-level racial disparities in credit card delinquencies between young adults living in majority-white and majority-Latinx communities widened by 0.4 percentage points by August 2023, representing a 10 percent increase in the gap (figure 4, see table B.5, for the full regression table). Until 2023,

[16] The shift in the community-level racial disparity in credit scores between young adults living in majority-white and majority-Native communities, while consistent with the trends observed for majority-Black and majority-Latinx communities, does not reach statistical significance at the $p < 0.05$ level because of the smaller sample size.

these disparities narrowed, with the largest decline occurring in August 2021 (2.1 percentage points, or 52.5 percent relative to February 2020).[17]

Decomposition of Community-Level Racial Disparities in Young Adults' Credit Health

In the findings section above, I find large and persistent community-level racial disparities in credit health between young adults living in communities of color and those living in majority white communities. These disparities may be due to several factors, including differences in income, educational attainment, employment status, or homeownership levels across communities, or could reflect structural and cumulative disadvantages from housing and other policies highlighted in previous research literature.

Using a threefold Oaxaca-Blinder decomposition, I find that common correlates of credit health and financial well-being, including community-level income, educational attainment, employment, and homeownership only explain half of the difference in mean credit scores between young adults living in communities of color and those living in majority white communities in February 2020 (figure 5). For example, only 14.8 points of the 67.0-point difference in mean credit scores between young adults living in majority Black and majority white communities can be explained by differences in endowments, or the level of observable characteristics for community-level education, income, employment, and homeownership in the reference group (reference group = majority white communities, see table 1). Similarly, a significant portion of the difference in mean credit scores between young adults living in majority Latinx and those living in majority white communities remains unexplained—there is a 33.5-point difference in mean credit scores, and 16.8 points are unexplained (see "coefficients" in table 2).[18]

[17] The change in community-level racial disparities in credit card delinquencies between young adults living in majority-white and majority-Native communities, while not statistically significant at the $p < 0.05$ level because of a smaller sample size, aligns with the trends observed in majority-Black and majority-Latinx communities. Evidence suggests a potential widening of disparities by August 2023, as detailed in the full regression tables in appendix B, table B.5.

[18] For young adults living in majority Native communities, the majority of the difference in mean credit scores between young adults living in majority Native and those living in majority white communities remains unexplained—there is a 75.0 point difference in mean credit scores, and 52.1 points are unexplained while 36.7 points of the difference in mean credit scores can be explained by differences in the level of income, educational attainment, employment, and homeownership in the reference group (see table B.6).

By including details on differences in housing price appreciation and residential segregation across communities that reflect differences in communities' wealth-building opportunities, I find that much of the mean difference in young adults' credit scores is explained for both majority Black and Latinx communities (figure 5 yellow bars).

To further break this down, I examine the portion of the mean difference in young adults' credit scores explained by differences in each community characteristic (figure 6). For majority Black communities, differences in levels of home appreciation were a significant explanatory factor but less so for young adults living in majority Latinx communities, where education played a larger explanatory role (figure 6). For example, differences in housing price appreciation levels between majority Black and majority white communities explained 31.8 points of the overall 67.5-point mean difference in young adults' credit scores (50.5 points of which are explained by differences in average characteristics of communities, see figure 6, top panel).

While I find compelling evidence that the inclusion of factors that capture differences in wealth-building opportunities across communities explains a greater share of racial disparities in credit health, there is still a portion left unexplained. Forty-one percent of the difference in mean credit scores between young adults living in majority white and majority Latinx communities remains unexplained and 25.1 percent remained unexplained for young adults living in majority Black communities (see table 1 and 2).

I find that there are still substantial differences in *returns* to education, income, employment, homeownership, housing wealth, and neighborhood diversity with respect to credit scores that likely reflect structural differences in the ability of young adults living in different communities to benefit from key investments in financial well-being (figure 7; Baradaran 2017; Gale 2021; Rothstein 2017). For example, for majority Latinx communities, differences in returns to income, employment, and housing price appreciation accounted for a substantial portion of mean difference in scores (figure 7, bottom panel). For young adults living in majority Black communities, differences in returns to housing price appreciation and residential segregation were substantial (figure 7, top panel).

Cohort-Level Trends in Credit Scores of Young Adults Between 2020-2023 and 2016-2019

The macroeconomic context young adults encountered between 2016 and 2019 and 2020 and 2023 varied substantially. From 2016 to 2019, inflation and unemployment remained low and stable, and consumers were increasing their levels of savings and consumption. In contrast, at the start of 2020, the U.S. economy experienced a short, but extraordinarily deep recession. In early 2020, unemployment reached a peak of 13.0 percent, coupled with significant earnings losses (Center for Budget and Policy Priorities, 2022). Compared to prior recessions, the severity of the initial shock (as measured by employment losses) during the pandemic recession was deeper, although the recovery was relatively swift (Center for Budget and Policy Priorities, 2023a; Center for Budget and Policy Priorities, 2023b). While unemployment rates lowered in the first year following the pandemic recession, additional economic volatility was introduced due to both (a) cycling shutdowns of businesses and increases in virus caseloads from 2020 to 2023 and (b) rapid increases in the price of essential goods starting in late 2021 (Center for Budget and Policy Priorities, 2023a; Center for Budget and Policy Priorities, 2023b). While there was substantial economic volatility, policymakers also infused large sums of money into the economy, expanded eligibility to key safety net programs, increased benefit levels of such programs, enacted consumer protections for non-payment of bills and loans, provided direct cash assistance to families, among other policies (Center for Budget and Policy Priorities, 2023a; Center for Budget and Policy Priorities, 2023b).

Given the high levels of unemployment and economic volatility observed during the pandemic recession from 2020 to 2023, we may expect that young adults' credit health would worsen in the years following the recession relative to young adults living in more stable economic times. This could be expected if young adults in 2020 experience higher levels of financial distress as a result of the recession and consequently struggle to repay debts and meet their day-to-day financial needs at the same time, which could result in worsening credit health. At the same time, large federal investments and changes in consumer behavior in living arrangements, savings, and consumption due to public health ordinances may have provided a protective buffer against the recession's second-order effects on young adults' credit in 2020, which may leave them with more personal and public resources to maintain a strong credit profile despite volatility.[19]

In comparing three-year trends in young adults' credit scores for the 2016 and 2020 cohort, I find that both cohorts see growth in their credit scores over time. Young adults (ages 20-23, 24-26, and 27-29) in the 2016 cohort experienced an average increase in credit scores one year, two years, and three years after the baseline period that varies between 0.5 and 4.8 points in year one, 3.9 and 10.3 points in year two, and 7.5 and 14.6 points in year three (relative to baseline scores, table 3). Similar young adults (ages 20-23, 24-26, and 27-29) in the 2020 cohort experience an average increase in credit scores one year, two years, and three years after the baseline period that varies between 13.5 and 16.1 points in year one, 18.7 and 22.2 points in year two, and 24.5 and 28.7 points in year three (relative to baseline scores, table 3).

However, three years after the baseline period, the 2020 cohort of young adults (ages 20-23, 24-26, and 27-29) experiences an average increase in credit scores between 14.1 and 17.0 points greater than similar young adults in the 2016 cohort (table 3). There is some small variability in the magnitude of such gains for young adults ages 24-26 and 27-29 (about 14 points), with a larger relative increase for young adults ages 20-23 (17.0 points) (table 3).

Cohort-Level Trends by Community Racial Demographic Composition

In exploring cohort-level trends in credit scores across communities, I find evidence that: (a) for all community demographics and cohorts, by the end of the three years, credit scores increase and (b) young adults living in communities of color in the 2020 cohort see larger credit score gains over three years compared with similar peers in the 2016 cohort.

Specifically, young adults ages 20-23, 24-26, and 27-29 living in majority Latinx communities in 2020 see a 22.7, 28.8, and 29.3 point increase in credit scores over three years while young adults living in these communities in the 2016 cohort see a 4.4, 14.0, and 13.9 point increase, respectively (table 3). For young adults ages 20-23, 24-26, and 27-29 living in majority

[19] During a macroeconomic shock like a recession, consumers' credit scores can change in a myriad of ways—consumers with low levels of liquidity and savings could turn to credit to make ends meet, driving up credit utilization and reducing credit scores; they could face financial pressures and fall behind on debt repayment, which would reduce their credit scores; or they could reduce consumption in ways that leave them using less credit and not seeking new forms of credit, which could increase credit scores. Similarly, during stable economic times, consumers may be easily able to repay existing debts—as they secure stable employment and face low-interest rates—increasing their scores, or they could take out high levels of debt, counting on economic conditions remaining rosy into the future, which could weaken their credit scores if they take on debt they can't easily repay.

Native American communities in 2020, credit scores rise 22.6, 34.0, and 32.6 points by 2023 while the 2016 cohort saw an increase of 9.2, 10.3, and 14.1 points over three years, respectively (table 3). Also, young adults ages 20-23, 24-26, and 27-29 living in majority Black communities in 2020 see a 25.9-, 34.9-, and 34.7-point gain in credit scores after three years while the 2016 cohort sees a 1.2-point reduction and 10.8- and 12.4-point gain over three years, respectively (table 3). For young adults in all communities, the sharpest gains in credit scores for the 2020 cohort happened over the first year of the pandemic.

Changes in Community-Level Racial Disparities in Credit Across Cohorts

In this section, I examine changes in community-level racial disparities in credit scores for each cohort (for young adults ages 20-23, 24-26, and 27-29).

I find that community-level racial disparities in credit scores between young adults living in majority Black communities and those living in majority white communities increases over three years for the 2016 cohort but decreases for the 2020 cohort—with the largest declines in year one (for all ages 20-23, 24-26, 27-29, table 4). I also find that community-level racial disparities in credit scores between young adults living in majority Latinx communities and those living in majority white communities remain stable over three years for those ages 24-26 and 27-29 in the 2016 cohort but marginally decrease for the 2020 cohort (table 4). Further, while such changes in these disparities for young adults (ages 20-23, 24-26, and 27-29) living in majority Native communities are not statistically significant at the $p<0.10$ level, the direction mirrors findings observed for majority Latinx communities (table 4).

Impacts of State-Level Utility Shutoff Moratoria and Extended Unemployment Insurance Programs on Young Adults' Credit Health

The observed improvements in credit health among young adults and the narrowing of community-level racial disparities in credit scores and credit card delinquencies early in the pandemic present an opportunity to explore the underlying mechanisms driving these trends.

During economic recessions, young adults experience larger and more persistent declines in employment and earnings than older adults, impacting their ability to establish long-term financial security and stability (Ellwood 1982; Kahn 2006; Rinz 2019; Rothstein 2021; Wachter 2020). Despite the significant levels of unemployment and financial distress during the pandemic, I found that young adults experienced improvements in their credit scores between

2020 and 2023 and declines in their credit card delinquencies in 2020 and 2021 before rebounding significantly in 2022 and 2023. This suggests a short-term buffering effect that shielded young adults against the negative impacts of the pandemic recession in the short term. Here are several plausible rationales for this:

- During the initial years of the pandemic, shifts in individual young adults' living arrangements and savings and consumption behaviors may have enabled consumers to amass resources and flexibility. This could have facilitated debt management, financial obligation fulfillment, and the ability to meet their day-to-day financial needs—thereby improving their credit early in the pandemic.
- On the other hand, recent research on the effects of pandemic-era federal and state policies suggests that these interventions may have reduced financial distress, ensuring families' financial security despite economic volatility (Andre et al. 2024, 2023; Karpman et al. 2021, 2022; Karpman and Acs 2020; Wheaton and Kwon 2022).

Understanding the mechanisms safeguarding young adults' credit health during this period could provide insight into which policies and practices could help young adults maintain financial stability during economic downturns. This could help ensure that future recessions do not exacerbate structural disparities in financial well-being. This section of the paper tests whether two state-level consumer protection and safety net policies contributed to improving young adults' credit health over the pandemic.

Utility Shutoff Moratoria

Utility shutoff moratoria prevented service providers from cutting off utilities because of nonpayment. Some but not all states implemented this protection for consumers, and the time such policies were active over the pandemic varied (figure 8). While active, these policies alleviated concerns about utility bill payment among young adults, ensuring continued access to essential services despite economic challenges (Martinchek and Warren 2020). With respect to credit health, we may expect the following:

- Utility shutoff moratoria could leave consumers with more economic resources to stay current on bills, which would improve their credit scores.

- Consumers who usually rely on credit cards to pay utility bills on time and avoid shutoffs may choose to prioritize other financial obligations during moratoria. As a consequence, credit card delinquency rates may decline.

Credit Scores

I found that utility shutoff moratoria increased young adults' credit scores by 0.57 points, representing a modest 0.09 increase in credit scores ($p < 0.01$, mean = 642.2; table B.7, model 4; figure 9).

Among young adults who did not benefit from other federal policies aiding homeowners and student loan holders, utility shutoff moratoria exhibited a larger impact, resulting in a 1.14 point increase in credit scores. However, this increase remained small in magnitude, reflecting a 0.15 percent increase in scores ($p < 0.01$, mean = 639.6; table B.7, model 5; figure 9).[20]

My analysis reveals that utility shutoff moratoria have more pronounced effects for young adults living in communities of color. There was a 1.58 point increase in credit scores for those living in majority-Black communities, a 1.64 point increase for those in majority-Latinx communities, and a substantial 5.00 point increase for those living in majority-Native communities ($p < 0.01$ for majority-Black and majority-Latinx, $p < 0.05$ for majority-Native; mean = 573.1 majority-Native, mean = 600.8 majority-Black, mean = 627.4 majority-Latinx; table B.8, models 3, 5, and 7, figure 9).

Credit Card Delinquencies

I found that utility shutoff moratoria were linked to a 0.18 percentage point, or 2.25 percent, decrease in young adults' credit card delinquencies ($p < 0.01$, mean = 7.97; table B.9, model 4; figure 10). For young adults without student loans and mortgages who may not benefit from federal forbearance policies, utility shutoff moratoria were associated with slightly larger declines in credit card delinquencies of 0.28 percentage points, or 2.6 percent ($p < 0.05$, mean =

[20] Testing for robustness in the contiguous county analysis, I did not find a statistically significant impact of utility shutoff moratoria on young adults' credit scores at the $p < 0.05$ level using pair-time and county fixed effects (for my preferred specification in the contiguous county analysis, see table B.11, model 6) but do find positive impacts on credit scores with county fixed effects (0.75 point increase, $p < 0.01$; table B.11, model 2). Similarly, among young adults living in bordering counties, utility shutoff moratoria were associated with a 0.61 point increase in credit scores, reflecting a 0.09 percent increase in scores ($p < 0.01$, mean = 642.9; table B.12).

10.5; table B.9, model 5; figure 10).[21] No significant evidence exists that utility shutoff moratoria were associated with statistically significant changes in credit card delinquencies for young adults living in specific communities of color. However, the direction of coefficients aligned with the impacts for young adults overall (table B.10; figure 10).[22]

Extended Unemployment Insurance Programs

Extended UI policies provide additional weeks of UI payments to individuals who have exhausted traditional UI benefits. Extended UI policies are activated when states meet predetermined criteria, which vary by state and capture their residents' economic distress and unemployment levels. The extended UI program has two levels: the regular 13-week extension and the 20-week benefit extension. These extensions are activated at different economic distress and unemployment thresholds, as defined by each state.

During the pandemic, all states enacted the extended UI regular program, though they had differing implementation and expiration dates. For example, fewer than half of the states had active extended benefits programs in December 2020, and no states had the benefits by April 2022. Importantly, extended benefits programs are only a small portion of the overall UI program, accounting for roughly 2.6 percent of all UI claims in 2021 (Center for Budget and Policy Priorities 2023a, 2023b). This analysis leverages variations in the implementation and expiration of extended UI benefits (both 13 and 20 weeks) to identify their policy impacts on young adults' credit scores and credit card delinquencies. It is important to note that the analysis presented below estimates the impact of the *extended* UI programs (13 and 20 weeks), not the overall impact of UI programs on young adults' credit health.

For young adults, UI programs may be especially beneficial, as they experienced disproportionately higher job losses and income disruptions during the pandemic and struggled to secure jobs at higher rates than older adults (Martinchek and Warren 2020; Martinchek 2020). As such, we may expect the following:

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[21] Testing for robustness in the contiguous county analysis, I found that utility shutoff moratoria were associated with a 0.28 percentage point decline in credit card delinquencies using pair-time and county fixed effects (for my preferred specification in the contiguous county analysis; table B.13, model 6), although this was only significant at the $p < 0.10$ level (mean = 9.05). I also found evidence of similar declines in credit card delinquencies among the sample of consumers in bordering counties of 0.22 percentage points ($p < 0.01$, mean = 7.87; table B.14).

[22] These findings cohere with Andre et al. (2024), which also examines the impact of state-level utility moratoria on consumer credit card delinquencies—which finds reductions in delinquencies across all consumers and stronger effects among consumers with subprime credit scores.

- Extended UI programs (both 13 and 20 weeks) may provide young adults with more economic resources over a longer period, helping them stay on time in repaying bills, which is the largest component of credit scores, thus increasing their scores.
- The prolonged economic support provided by extended UI programs (both 13 and 20 weeks) may contribute to young adults' ability to stay current on credit card bills and repay charges.

Credit Scores

I found that extended UI benefit programs (20 weeks) were associated with a 0.34 point increase in credit scores among young adults ($p < 0.01$, mean = 642.2; table B.7, model 4; figure 11). While statistically significant, this only reflected a 0.04 percent increase in credit scores.[23] In contrast, the shorter extended benefit UI program (13 weeks) was associated with a 0.22 point increase ($p < 0.05$, mean = 642.2; table B.7, model 4; figure 12).

For young adults without student loans or mortgages who are less likely to benefit from federal forbearance programs during the pandemic, extended UI programs were associated with marginal increases in credit scores of 0.46 points for both the 13-week and 20-week program ($p < 0.01$, mean = 639.6; 0.07 percent increase in credit scores; table B.7, model 5; figures 11 and 12).

For young adults living in majority-Latinx communities, extended UI benefit programs (13 weeks) were associated with a 1.14 point decrease in credit scores ($p < 0.05$, mean = 627.4; table B.8, model 7; figure 12). There were no statistically significant impacts for young adults living in majority-Native communities and majority-Black communities (table B.8, model 3 and model 5; figure 12).

Credit Card Delinquencies

I found that 13-week and 20-week extended UI benefit programs reduced young adults' credit card delinquencies by 0.28 percentage points and 0.13 percentage points, respectively ($p < 0.01$

[23] Testing for robustness in the contiguous county analysis, I did not find a statistically significant impact of extended UI benefit programs on young adults' credit scores at the $p < 0.05$ level using pair-time and county fixed effects, although the direction does match the main results (table B.15, model 6, for 13-week extended UI programs; table B.16, model 6 for 20-week extended UI programs). When examining policy impacts among young adults living in bordering counties, extended benefits 20-week programs were associated with a 0.33 point increase in credit scores, matching the direction of the main findings ($p < 0.01$, mean = 642.0; table B.18) but were not statistically significant for 13-week programs (table B.17).

and $p < 0.05$ respectively, mean = 7.97; table B.9, model 4; figures 13 and 14).[24] This reflected a 3.5 percent and 1.6 percent decline in credit card delinquencies for young adults in states with active 13- and 20-week extended UI benefit programs.

For young adults without student loans and mortgages, 13-week and 20-week extended UI benefit programs reduced young adults' credit card delinquencies by 0.29 percentage points and 0.22 percentage points, respectively (2.5 and 2.0 percent decline in delinquencies respectively, $p < 0.01$, mean = 10.5; table B.9, model 5; figures 13 and 14).

I also found that 13-week extended UI benefit programs were associated with stronger effects for young adults living in majority Black communities, while these impacts were null for longer (20-week) programs. The 13-week extended UI benefit programs reduced credit card delinquencies by 1.54 percentage points among young adults living in majority-Black communities ($p < 0.01$ respectively, mean = 16.90 majority-Black; table B.10, models 3 and 5, figure 14). This reflected a 9.0 percent decline for young adults living in majority-Black communities—a qualitatively large declines in credit card delinquency rates for young adults living in these communities of color.[25]

Discussion

In this section, I draw from broader literature to contextualize and discuss empirical findings.

[24] Testing for robustness in the contiguous county analysis, I did not find a statistically significant impact of extended UI benefit programs (13 week and 20 week) on young adults' credit card delinquencies at the $p < 0.05$ level using pair-time and county fixed effects (my preferred specification, see table B.19, model 6, and table B.20, model 6) but did find positive impacts on credit card delinquencies with county fixed effects for 13-week programs (0.36 percentage point increase, $p < 0.01$; table B.19, model 2). I also found that extended UI benefit programs (13 week and 20 week) were associated with a 0.31 and 0.17 percentage point decline (or 3.9 percent and 2.1 percent decline) in credit card delinquencies among the sample of consumers in bordering counties ($p < 0.01$ and $p < 0.05$, respectively, mean = 7.92; tables B.21 and B.22).

[25] I also found weak evidence that extended UI benefit programs (13 weeks) were associated with a small increase in credit card delinquencies of 0.69 percentage points (mean = 12.22) for young adults living in majority-Latinx communities, although this was not statistically significant at the $p < 0.05$ level (table B.10, figure 14). There were no statistically significant impacts for young adults living in majority-Native communities (table B.8, model 3; figure 12).

Pandemic-Era Improvements in Credit Health Warrant Further Exploration

I find evidence of improved credit health (in terms of increases in credit scores and declines in credit card delinquencies) among young adults ages 20-29 during the first year and a half of the pandemic, despite high levels of unemployment and economic volatility.

There may be several reasons that credit health improved for young adults early in the pandemic. For example, at the start of the pandemic, public health guidelines induced a significant decline in consumers' consumption and spending (Klitgaard & Higgins, 2023). During this period, consumers spent less on entertainment, eating out, shopping, and alcohol and started to accrue savings—and many young adults moved home to live with their parents, further curbing expenses (Klitgaard & Higgins, 2023; Parker et al., 2022). Such changes in young adults' consumption and savings habits could leave them with more resources to stay current on debt payments and bills, which is a significant portion of credit scoring algorithms.

Another possible explanation for improving credit health during the pandemic could be federal and state policies that supported consumer's financial well-being. Recent research identifies causal links between consumers' financial and credit health improvements and federal and state policies—which is also further probed in this paper's RQ4 analyses (Martinchek, 2024b; Andre et al., 2023, 2024; Cherry et al., 2021; Ganong et al., 2022).

Despite these early pandemic gains, I find evidence of growing credit card delinquencies—especially among young adults living in communities of color—after late 2021. Young adults may have found it challenging to repay credit card debt during late 2021, 2022, and 2023 as (a) fewer active federal and state policy supports left them with lower levels of public supports to meet their financial needs, as many of these policies expired in late 2021 and early 2022; (b) savings of young adults, which spiked in the first years of the pandemic, began to be spent down at the same time that prices of many essential goods increased; and (c) increasing credit card interest rates increased the cost of unpaid credit card bills; which may have meant that it was easier for young adults to fall – and stay – behind on credit card payments as they became more unaffordable (Martinchek et al., 2023; Haughwout et al., 2023; Klitgaard & Higgins, 2023; Parker et al., 2022). Young adults living in communities of color may have been disproportionately impacted by such dynamics and experienced a greater squeeze on their budgets as they are also likely to have fewer personal and public resources to effectively absorb these price increases (Martinchek et al., 2023). If young adults living in communities of color experienced new or persistent income shortfalls, they may have increasingly relied on credit to fill the gaps but struggled to repay credit card bills on time as borrowing costs similarly rise (Martinchek et al., 2023; Haughwout et al., 2023; Jayashankar & Murphy, 2023).[26]

Persistent Community-Level Racial Disparities in Credit Likely Reflect Differences in Wealth-Creation Opportunities

As expected, I find that young adults living in communities of color (majority Black, majority Latinx, and majority Native communities) experience worse credit scores at the beginning of the pandemic and throughout, relative to young adults living in majority white communities. Further, while community-level racial disparities show some signs of narrowing marginally in the first year and a half following the start of the pandemic, these improvements are small relative to the overall magnitude of the disparity. Additionally, there are some signs that such reductions in community-level racial disparities in credit health are eroding and reversing by 2023—especially in terms of delinquencies, which can be an indicator of financial distress.

These persistent community-level racial disparities in credit health likely reflect structural vulnerabilities that leave young adults living in communities of color more susceptible to the negative impacts of recessions (Faber, 2019; Taylor, 2019; Weller & Hanks, 2018; Baradaran, 2017; Rothstein, 2017). I find that differences in education, income, homeownership, and employment between communities only explain a relatively small portion of the difference in credit scores between young adults living in communities of color and those living in majority white communities. By including details on differences in housing price appreciation and residential segregation across communities that reflect differences in communities' wealth-building opportunities, I find that much of the mean difference in young adults' credit scores is explained for both majority Black and Latinx communities. This suggests differences in wealth-building opportunities across communities may meaningfully shape young adult residents' own financial well-being in important ways and could capture an important pathway by which racial disparities are entrenched and perpetuated. These empirical results align with prior research that

[26] It is also important to note that young adults with access to a credit card are on average more financially advantaged than peers who do not have access to a credit card—because they can borrow money during economic emergencies at lower rates and have credit as a potential option to respond to financial emergencies—as evidenced by the fact that young adults in the analytic sample have credit scores over 80 points higher than peers without credit cards (Elliott & Lowitz, 2019,). As such, it is important to contextualize that the empirical findings and explanations presented here reflect a relatively more financially advantaged group of young adults than the overall population.

suggests that differences in wealth-building opportunities and access to credit may be an omitted factor that could meaningfully explain racial disparities in credit (Baradaran 2017; Dymski 2009; Gale 2021; Goodstein and Rhine 2017; Katznelson 2005; Markley et al. 2020; Martinchek forthcoming; McKenna 2008; Rothstein 2017; Taylor 2019; Wyley et al. 2009). Despite this, there are still substantial differences in returns to education, income, employment, homeownership, housing wealth, and neighborhood diversity with respect to credit scores that likely reflect structural differences in the ability of residents of different communities to benefit from wealth-building opportunities that suggest policy action could be helpful to equalize wealth-building opportunities (Baradaran 2017).

Young Adults in 2020 Saw Larger Gains in their Credit Health Over A Three-Year Period

I find that over three years, young adults (ages 20-23, 24-26, and 27-29) in both the 2016 and 2020 cohorts see gains in credit scores, but young adults in 2020 see a 49.1 to 69.3 percent larger increase in credit scores relative to similar peers in 2016. A possible explanation for larger improvements in three-year credit health outcomes for the 2020 cohort may be the provision of expansive federal and state benefits or substantial changes in living arrangements and saving and consumption behaviors during this time. It is possible that policies may have helped young adults cope with pandemic economic pressures without having to turn to mainstream credit to meet their financial needs (Andre et al., 2023, 2024; Cherry et al., 2021; Ganong et al., 2022; Martinchek, 2024b). For example, policies that enabled payment suspensions for key costs (e.g., student loans) and those that provided more economic resources (such as enhanced unemployment insurance programs, SNAP emergency allotments, and Economic Impact Payments, among others) may have enabled young adults to manage their finances without drawing on their private safety nets despite ongoing economic volatility and instability (MacDonald et al., 2021; Martinchek, 2020; Martinchek, 2024b). If this is the case, and young adults used an expanded safety net to repay debt and meet their financial needs without relying on credit, we would expect credit scores to improve more substantially than they would otherwise, and more so than they may have in calmer macroeconomic circumstances (Belise, 2020; Perez-Lopez & Monte, 2021).

Further, I also find that community-level racial disparities in credit scores between young adults (ages 20-23, 24-26, and 27-29) living in majority Black and Latinx communities and those living in majority white communities *increases or remains stable* over a three-year period for the 2016 cohort but *decreases* for the 2020 cohort *most sharply in the first year before beginning to regress to baseline levels* for all ages and communities. These results suggest that over the pandemic (from 2020 to 2023), community-level racial disparities in credit health between young adults living in majority white communities and those living in communities of color narrowed, albeit *only slightly relative to the magnitude of the overall disparity* and even more interestingly, they *show signs of rebounding in year three (August 2023)*. It is possible that policies and practices that helped young adults cope with pandemic-related economic pressures benefitted young adults living in communities of color more substantially and helped them keep up with peers living in majority white communities during the recovery. Despite these gains, significant racial disparities in credit health between young adults living in majority white communities and those living in communities of color persisted in both the 2016 and 2020 cohorts.

State-Level Policies May Manage Dynamic Risks to Racial Equity Postpandemic

As expected, utility shutoff moratoria and extended UI programs have small yet positive impacts on young adults' credit health, as measured by credit scores and credit card delinquencies. These findings support the notion that utility shutoff moratoria may alleviate pressures associated with repaying utility bills to avoid shutoffs, while extended UI programs may furnish young adults with prolonged economic resources, enabling them to stay current on bills and debt obligations. While the empirical findings in this study are consistent with these hypotheses, this study does not directly test these explanations within its scope, making the evidence suggestive rather than conclusive.[27]

[27] It is also crucial to contextualize the impacts of pandemic-era consumer protection and safety net policies, such as utility shutoff moratoria and extended UI programs. These policies were designed to help consumers weather volatile economic circumstances, offering support during job loss, health emergencies, and unexpected expenses. However, it's important to recognize that their primary aim was not to close racial gaps in credit health or tackle the root causes of such disparities (Traub 2021).

While my findings are statistically significant, many of the effects measured in this study are small in magnitude, suggesting they may not reflect measurable improvements across the board *for all young adults*—whether it be in young adults' ability to access credit, reduce their borrowing costs, or alleviate acute financial distress. However, not all young adults participated in these programs. The policy impact estimates presented in this study reflect ITT estimates, providing insights into the impacts for *all* young adults with a credit record living in a state where a policy was active, irrespective of individual participation.[28]

Conclusion

Overall, this study highlights the presence of persistent community-level racial disparities in young adults' credit health, decomposes these differences, explores trends in young adults' credit health over the pandemic across different community compositions, and quantifies the impact of different state-level consumer protection and safety net policies on young adults' credit health.

This empirical analysis suggests that community-level racial disparities in credit health are substantial and qualitatively meaningful—affecting young adults' ability to borrow at affordable rates, access mainstream credit, and participate in future wealth-building opportunities. I find that these racial disparities in young adults' credit scores are likely driven by

[28] To better understand the potential magnitude of the impact of these policies on young adults who did use these programs, I employed the Bloom adjustment (Bloom 1984) to rescale the ITT estimates generated in this study by the share of young adults who used these programs. In the credit bureau data, I was not able to observe data on whether consumers in the sample took up each of the policies, so I used the Bloom (1984) adjustment to rescale the ITT estimates by the share of the population that likely benefited from the offered policies. In computing this adjustment, I made two assumptions: (1) no consumers in the nonimplementing states received the policy in the period of interest; and (2) no sampling variability existed in the share of consumers who did not take up the policy—which could bias estimates (Litwok and Peck 2019). I used the following data: (a) the share of young adults (ages 20 to 29) who reported they had problems paying their utility bill from the Urban Institute Well-Being and Basic Needs Survey (9.9 percent in 2020 and 11.2 percent in 2021) and (b) the share of young adults who received UI from the US Census Bureau Household Pulse Survey as analyzed by Carey et al. (2021) and scaled by the share of UI claims for extended benefits programs from the Department of Labor's Unemployment Weekly Claims Report (18.2 percent of young adults ages 18 to 24 and 20.9 percent of young adults ages 25 to 34 received UI benefits, and 2.6 percent of all UI claims were filed for extended benefits, which results in 0.47 percent and 0.54 percent as the adjustment factors to be used for the Bloom (1984) adjustment). Through this adjustment, I found that state-level utility shutoff moratoria and extended UI programs indeed had a meaningful and positive impact on the credit health of the young adults who used them. For example, utility shutoff moratoria were associated with an estimated 1.82 to 1.61 percentage point decrease in credit card delinquencies (22.8 to 20.2 percent) and an estimated 5.85 to 5.17 point increase in credit scores (less than 1 percent) for young adults who may have benefited from these protections as they experienced challenges repaying their utility bills. Similarly, young adults taking advantage of extended UI programs likely experienced more profound declines in credit card delinquencies and increases in credit scores.

differences in wealth-building opportunities across communities. As such, addressing disparities in young adults' credit health likely necessitates policies that directly confront the underlying issues of wealth-building opportunities and credit access disparities between communities. For example, policies such special purpose credit programs that enable banks to offer credit on favorable terms to borrowers who have suffered economic disadvantage and postal banking programs designed to directly tackle challenges of financial exclusion present in communities of color by expanding banking options available could act to equalize access to affordable credit across communities (Friedline et al 2021; Long and Pressman 2023; Choi et al. 2022). Other policies that address unequal returns to investments and wealth-building opportunities across communities, such as policies that protect against discrimination in property valuation and appraisals and provide debt relief for education debt– can also enable consumers of color to equally benefit from asset investment opportunities in housing and education (Williamson, 2020; Rothwell & Perry, 2022; Zonta, 2019; Perry et al., 2021; Mishory et al., 2019; Weller & Figueroa, 2021).

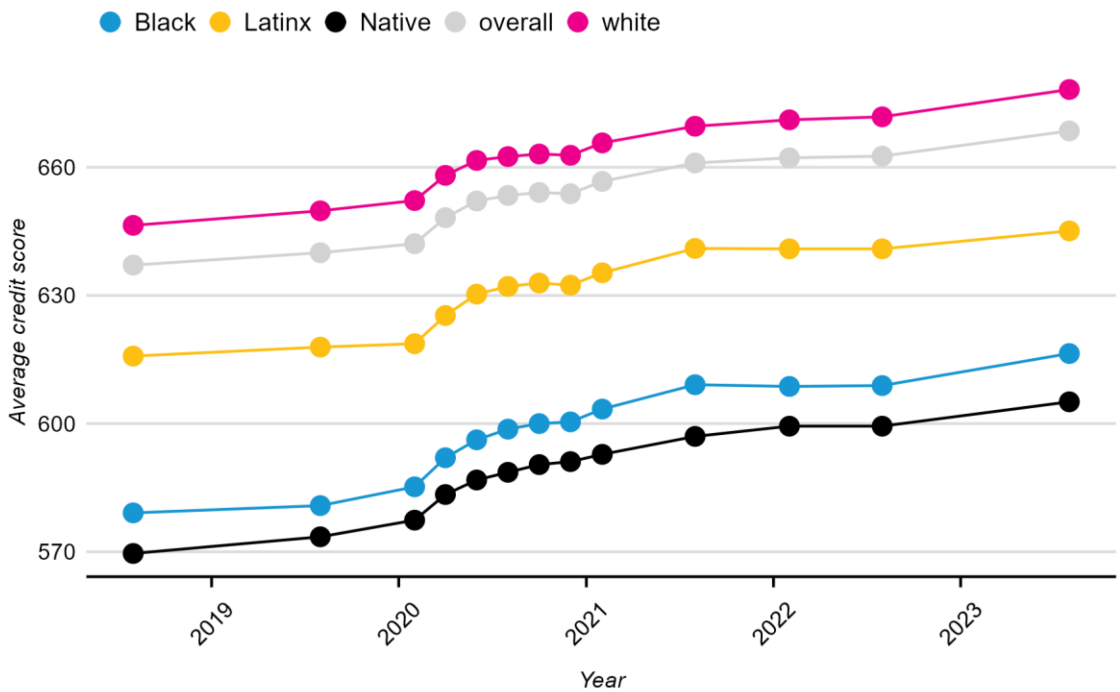
This study also finds evidence that pandemic-era policies designed to insulate consumers from adverse impacts associated with the pandemic recession effectively helped young adults preserve strong credit. Given young adults' unique vulnerabilities to recessions and the potential for community-level racial inequities to widen postrecession, it is important to understand the effectiveness of pandemic-era policies for young adults starting their financial lives and whether these policies prevented widening inequities across communities. Despite high levels of unemployment and economic volatility during the first year and a half of the pandemic, young adults' credit scores improved and credit card delinquencies declined. Such gains in credit scores even surpassed credit score increases observed in less volatile economic times. While changes in young adults' living arrangements and savings and consumption behaviors may contribute to trends in improving credit health, I also find that state-level consumer protection and safety net policies contributed to improvements. State-level utility shutoff moratoria marginally improved young adults' credit scores and decreased their credit card delinquency rates by 2.2 percent. Similarly, extended UI programs led to improvements in credit scores and declines in delinquencies, with 13-week programs linked to more significant improvements for young adults living in communities of color. These findings suggest that state-level consumer protection and safety net policies likely helped young adults weather the pandemic recession, easing bill repayment pressures and bolstering economic resources.

While I find evidence that state-level policy interventions likely helped young adults preserve strong credit health in the aftermath of the pandemic recession, I also find evidence of increasing economic distress among young adults after late 2021, when many state and federal level safety net and consumer protection policies expired. Increasing delinquencies in 2023 also widened community-level racial inequities in credit health and debt, leaving young adults living in communities of color in a worse financial position than their peers in more-affluent, majority-white communities. For example, credit card delinquencies increased among all young adults between 2020 and 2023, but those increases were larger for young adults living in majority-Black and majority-Native communities. Delinquencies climbed by 22.6 percent and 31.9 percent among young adults in Black and Native communities, respectively, compared with 17.6 percent among those in majority-white communities. This suggests that young adults are having trouble meeting their financial obligations in 2023 and may need additional supports to regain financial stability—and maintain it. It is possible that rising inflation for essential goods, especially groceries, and eroded savings may mean that young adults may be under greater economic pressure in meeting their basic needs and may have lower buffers to absorb unexpected expenses and respond effectively to financial emergencies.

Figures and Tables (in order of appearance)

Figure 1: Credit Scores Improved for Young Adults through the Pandemic

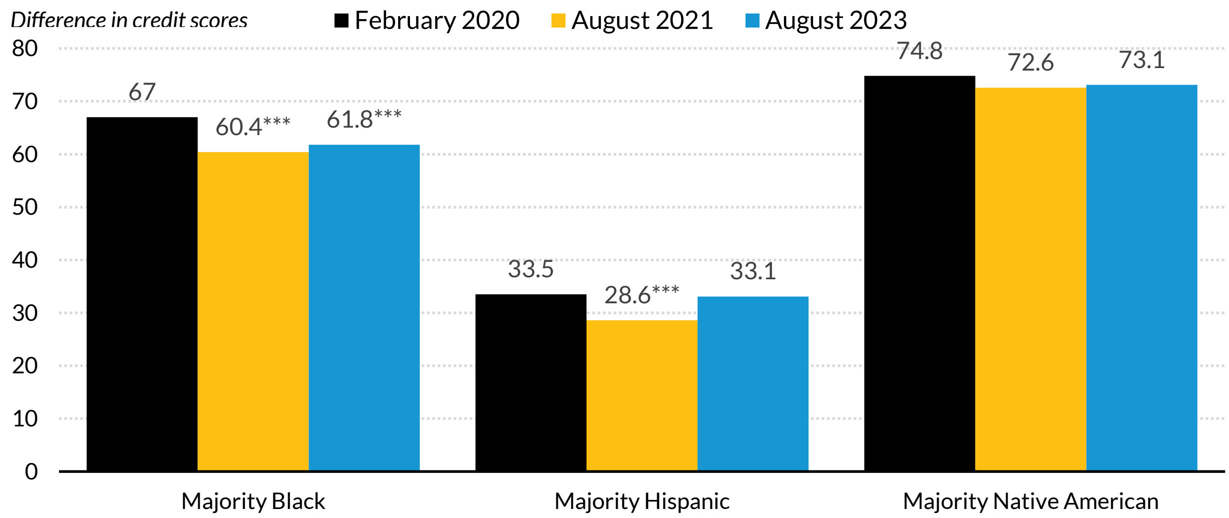
Average credit scores of young adults (ages 20 to 29) living in different communities, 2018–23



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays average VantageScores (300 to 850) of young adults ages 20 to 29 with a credit bureau record between August 2018 and August 2023 by community demographic composition. Black, Native, Latinx, and white communities are defined as Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey.

Figure 2: Community-Level Racial Disparities in Credit Scores Rebound to Pre-Pandemic Levels

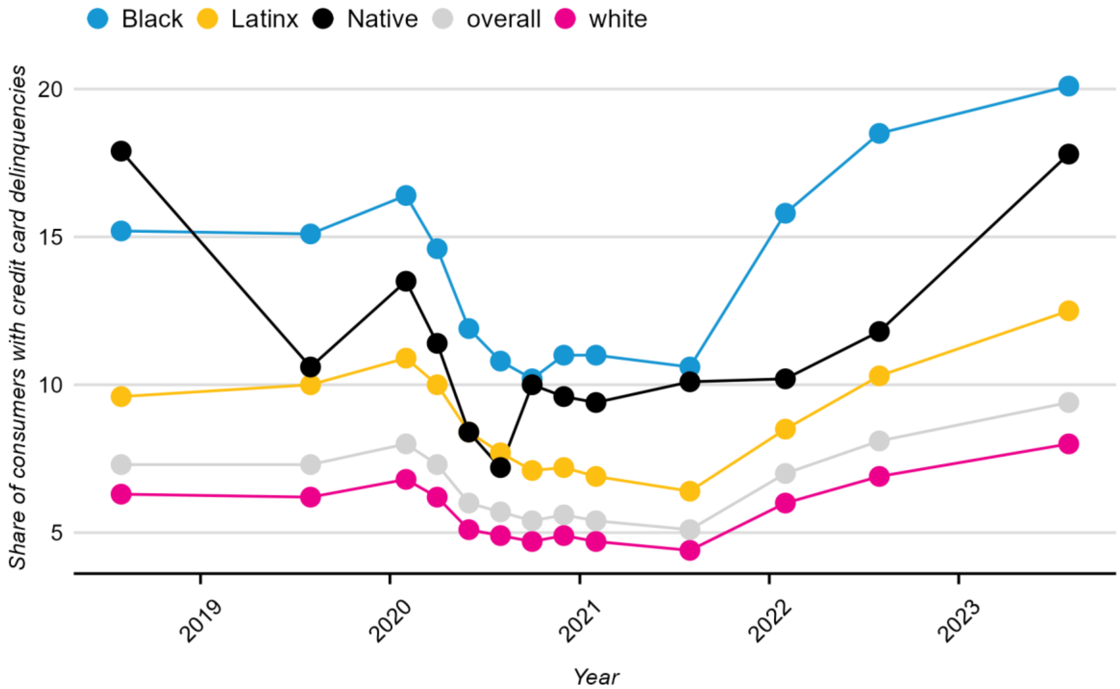
Average difference in credit scores between young adults ages 20-29 living in communities of color and those living in majority White communities; regression-adjusted



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays the community-level racial disparity in average VantageScores (300 to 850) of young adults ages 20 to 29 with a credit bureau record in February 2020, August 2021, and August 2023. Black, Native, Latinx, and white communities are defined as Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey.

Figure 3: Young Adults' Credit Card Delinquencies Declined Rapidly in the First Year of the Pandemic before Rising to Prepandemic Levels

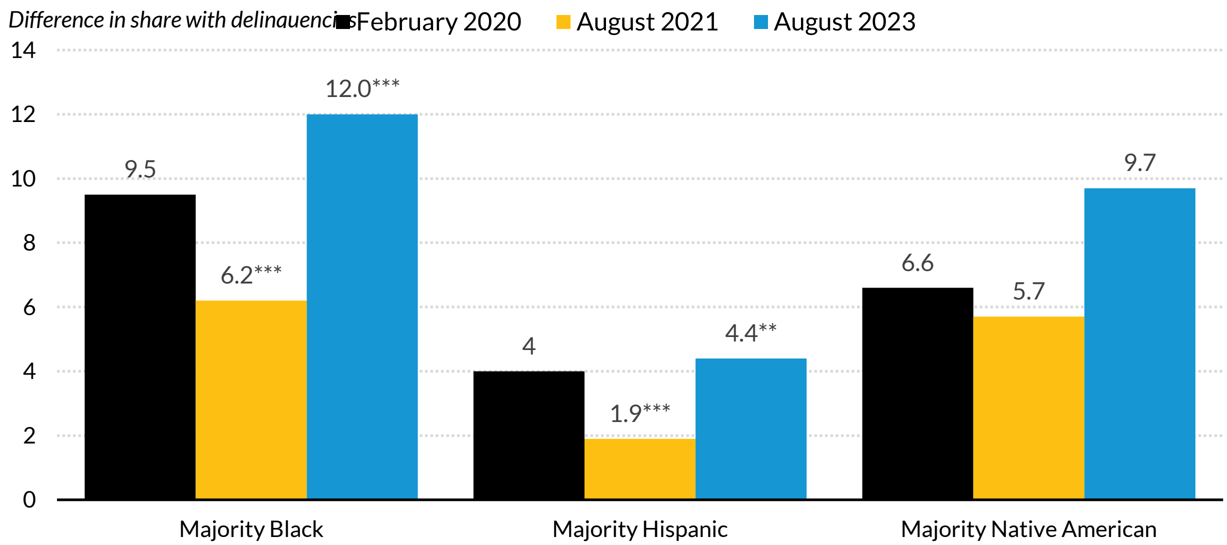
Share of young adults (ages 20 to 29) with a delinquent credit card payment, among consumers with a credit card, by community demographic composition from 2018 to 2023



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays the share of young adults ages 20 to 29 with a credit bureau record and at least one credit card who were 30 or more days behind on their credit card bill, by community demographic composition. Black, Native, Latinx, and white communities are defined as Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey.

Figure 4: Community-Level Racial Disparities in Delinquencies Widen by 2023

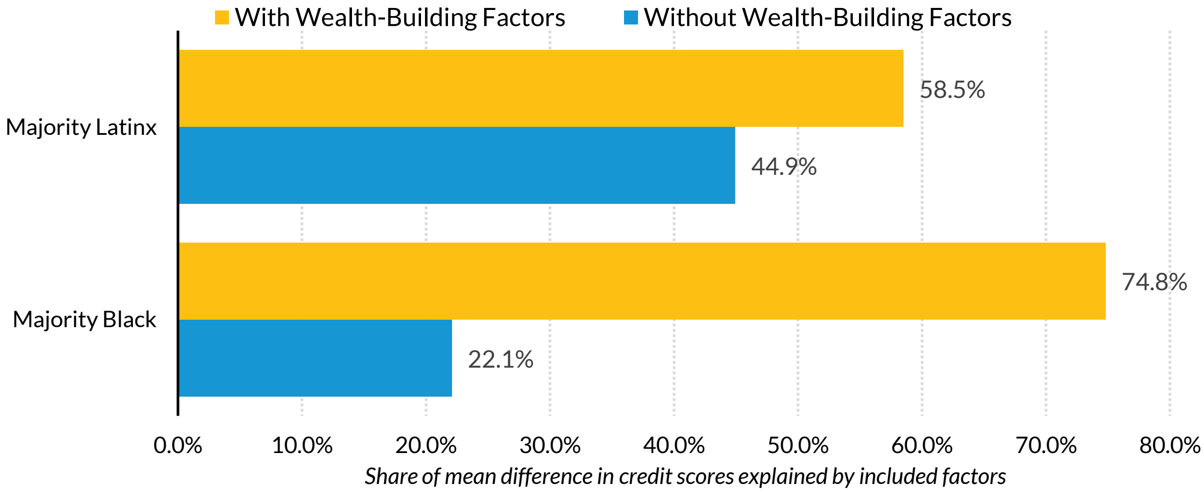
Average difference in the share of young adults 30+ days behind on credit card bills between those living in communities of color and those living in majority White communities; regression-adjusted



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays the community-level racial disparity in the share of young adults ages 20 to 29 with a past-due credit card bill (30+ days) in February 2020, August 2021, and August 2023. Black, Native, Latinx, and white communities are defined as Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey.

Figure 5: Including Differences in Community-Level Wealth-Building Opportunities Explains a Greater Share of Racial Disparities in Credit Scores

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

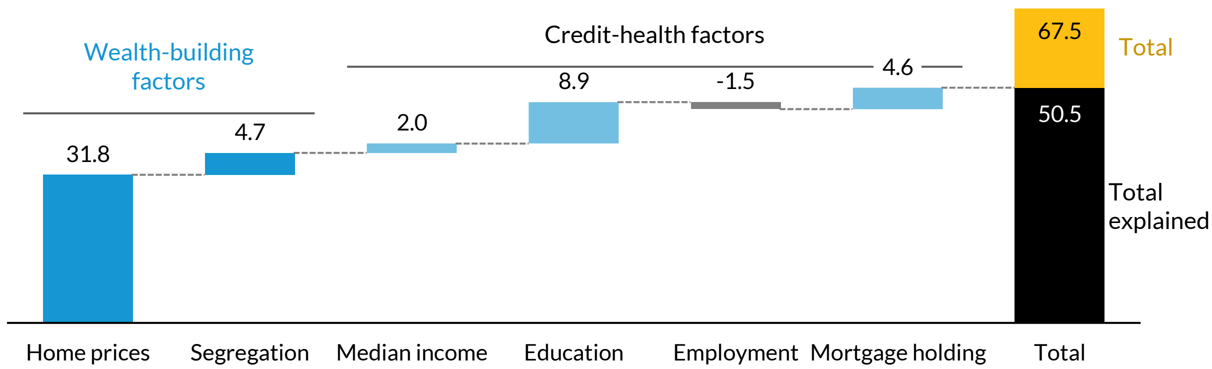


Source: Author's analysis of Urban Institute credit bureau data, American Community Survey data, and Mobility Metrics data (as published in Martinchek 2024b) in two separate threefold Oaxaca-Blinder decompositions.
Notes: This figure shows to what extent the difference in mean credit scores between young adults living in communities of color and those living in majority white communities (where majority white communities are the reference group) is explained by differences in levels of a set of predictors. For the blue bars, the set of predictors includes community-level (zip-code) data on educational attainment, median incomes, employment status, and mortgage ownership. For the yellow bars, all of these predictors plus measures of housing price appreciation by race and ethnicity and residential segregation by race and ethnicity are included. Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020.

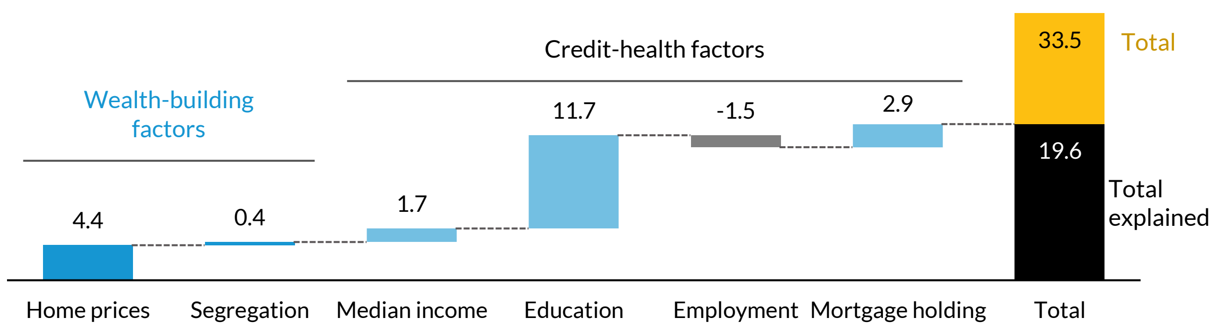
Figure 6: Racial Disparities in Credit Scores Largely Due to Differences in Wealth-Building Opportunities

Share of mean difference in young adults' credit scores explained by average characteristics of communities

Panel A: Majority Black communities



Panel B: Majority Latinx communities

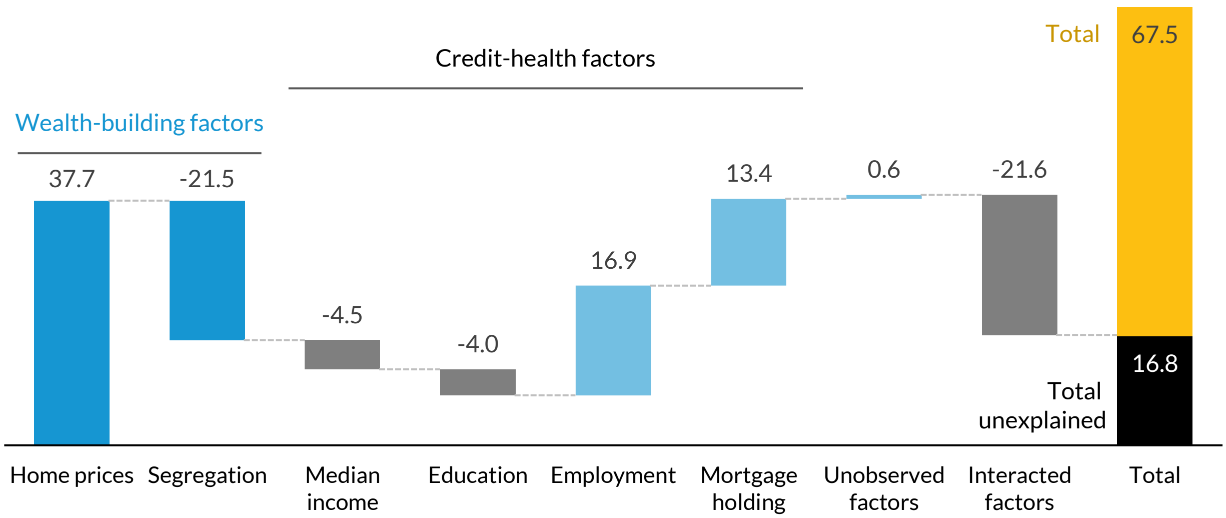


Source: Author's analysis of Urban Institute credit bureau data, American Community Survey data, and Mobility Metrics data (as published in Martinchek 2024b) in a threefold Oaxaca-Blinder decomposition.
Notes: This figure shows to what extent the difference in mean credit scores between young adults living in communities of color and those living in majority white communities (where majority white communities are the reference group) is due to differences in levels of a set of predictors. This plot specifically breaks down the effect of specific predictors' levels on differences in young adults' mean credit scores across communities. The predictors in this model include educational attainment, median income, employment status, homeownership (mortgage holding), home price appreciation by race/ethnicity, and neighborhood diversity for different racial and ethnic groups. Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020.

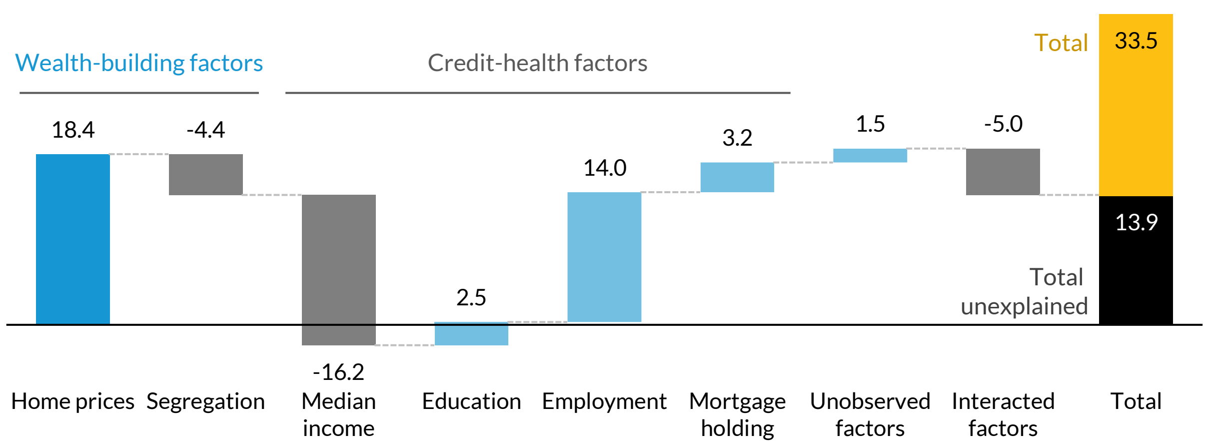
Figure 7: Racial Disparities in Credit Scores Also Capture Differences in Returns to Investments

Share of mean difference left unexplained by differences in returns to factors, unobserved factors, and interactions

Panel A: Majority Black communities



Panel B: Majority Latinx communities



Source: Author's analysis of Urban Institute credit bureau data, American Community Survey data, and Mobility Metrics data (as published in Martinchek 2024b) in a threefold Oaxaca-Blinder decomposition.
Notes: This figure shows to what extent the difference in mean credit scores between young adults living in communities of color and those living in majority white communities (where majority white communities are the reference group) is due to differences in returns of a set of predictors. This plot specifically breaks down the effect of specific predictors' returns as well as the impact of unobserved and interacted factors on differences in young adults' mean credit scores across communities. The predictors in this model include educational attainment, median income, employment status, homeownership (mortgage holding), home price appreciation by race/ethnicity, and neighborhood diversity for different racial and ethnic groups. Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020.

Table 1: Differences in Young Adults' Credit Scores Are Shaped by Differences in Wealth-Building Opportunities Across Communities

Oaxaca-Blinder (OB) Decomposition for Majority Black Communities Relative to Majority White Communities

	ACS Variables Only	ACS and Mobility Metrics Data
OVERALL		
Mean Credit Score for Majority White Communities	652.2485***	653.0711***
Mean Credit Score for Majority Black Communities	585.1771***	585.5673***
Difference in Means	67.07143***	67.50378***
Difference in Means Due to Endowments	14.81388***	50.59294***
Difference in Means Due to Coefficients	48.14564***	38.5852***
Difference in Means Due to Interactions	4.11191***	-21.67436***
ENDOWMENT EFFECTS BY COVARIATE		
Median Household Income	2.386173***	1.970651***
Share with a Bachelors Degree or Higher	9.280086***	8.917035***
Share Employed	-1.358235***	-1.4524***
Share with a Mortgage	4.505852***	4.627719***
Home Price Appreciation		31.82859***
Residential Segregation		4.70135***
COEFFICIENT EFFECTS BY COVARIATE		
Median Household Income	-15.71706***	-4.474469**
Share with a Bachelors Degree or Higher	-1.082041	-4.008429***
Share Employed	29.38484***	16.90442***
Share with a Mortgage	3.199034	13.37081***
Home Price Appreciation		37.78443***
Residential Segregation		-21.5738***
_cons	32.36086***	0.5822358
INTERACTION EFFECTS BY COVARIATE		
Median Household Income	5.605039***	1.606361**
Share with a Bachelors Degree or Higher	0.4078326	1.543901***
Share Employed	-1.472843***	-0.8432894***
Share with a Mortgage	-0.428118	-1.781803***
Home Price Appreciation		-13.43686***
Residential Segregation		-8.762672***

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows output from a three-way Oaxaca-Blinder decomposition, which decomposes the difference in mean credit scores between young adults living in majority White and majority Black communities. The covariates included in the model on column 1 are age-specific rates of employment, mortgage ownership, income, and educational attainment, measured at the ZCTA level in the 5-year 2015-2019 American Community Survey. Column includes all of these covariates as well as measures of housing price appreciation and residential segregation by race and ethnicity from Urban Institute's Mobility Metrics dataset Majority White communities are the reference group. Majority Black, Latinx, White, and Native American communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). Differences in means are measured in points.

Table 2: Differences in Young Adults' Credit Scores Are Shaped by Differences in Wealth-Building Opportunities Across Communities

Oaxaca-Blinder (OB) Decomposition for Majority Latinx Communities Relative to Majority White Communities

	ACS Variables Only	ACS and Mobility Metrics Data
OVERALL		
Mean Credit Score for Majority White Communities	652.249***	652.9458***
Mean Credit Score for Majority Black Communities	618.695***	619.376***
Difference in Means	33.5537***	33.56981***
Difference in Means Due to Endowments	15.1069***	19.65922***
Difference in Means Due to Coefficients	16.8236***	18.91199***
Difference in Means Due to Interactions	1.62327***	-5.001407***
ENDOWMENT EFFECTS BY COVARIATE		
Median Household Income	1.65124***	1.780203***
Share with a Bachelors Degree or Higher	11.9778***	11.67869***
Share Employed	-1.497***	-1.497371***
Share with a Mortgage	2.97482***	2.947847***
Home Price Appreciation		4.39561***
Residential Segregation		0.3542486**
COEFFICIENT EFFECTS BY COVARIATE		
Median Household Income	-17.504***	-16.21191***
Share with a Bachelors Degree or Higher	4.29888***	2.501881**
Share Employed	7.77508**	14.03453***
Share with a Mortgage	1.98819	3.17941
Home Price Appreciation		18.35963***
Residential Segregation		-4.439732***
_cons	20.2658	1.488193
INTERACTION EFFECTS BY COVARIATE		
Median Household Income	4.31977***	3.986689***
Share with a Bachelors Degree or Higher	-2.0913***	-1.219196**
Share Employed	-0.4295**	-0.7640336***
Share with a Mortgage	-0.1757	-0.2775677
Home Price Appreciation		-4.864041***
Residential Segregation		-1.863257***

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows output from a three-way Oaxaca-Blinder decomposition, which decomposes the difference in mean credit scores between young adults living in majority White and majority Latinx communities. The covariates included in the model on column 1 are age-specific rates of employment, mortgage ownership, income, and educational attainment, measured at the ZCTA level in the 5-year 2015-2019 American Community Survey. Column includes all of these covariates as well as measures of housing price appreciation and residential segregation by race and ethnicity from Urban Institute's Mobility Metrics dataset Majority White communities are the reference group. Majority Black, Latinx, White, and Native American communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). Differences in means are measured in points.

Table 3: Young Adults in 2020 See Sharper Gains in Three-Year Credit Scores Than the 2016 Cohort

Summary Table of Average Credit Score Outcomes by Cohort and Year for Different Communities for Young Adults Ages 20-23, 24-26, 27-29 in the Matched Sample

	Ages 20-23	Ages 24-26	Ages 27-29
Majority Black Communities			
2016 Cohort 3-Year Increase	-1.2	10.8***	12.4***
2020 Cohort 3-Year Increase	25.9***	34.9***	34.7***
Majority Latinx Communities			
2016 Cohort 3-Year Increase	4.4***	14.0***	13.9***
2020 Cohort 3-Year Increase	22.7***	28.8***	29.3***
Majority Native Communities			
2016 Cohort 3-Year Increase	9.2*	10.3***	14.1***
2020 Cohort 3-Year Increase	22.6*	34.0***	32.6***

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows regression output of the average difference in weighted credit scores over a three-year period between young adults ages 20-23, 24-26, and 27-29 in 2016 relative to similarly aged young adults in 2020. Majority Black, Latinx, White, and Native American communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. The sample includes consumers with a credit bureau record that are similar in age and baseline credit scores across cohorts. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p<0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p<0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p<0.10$ level. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be unlikely to be approved for new credit (Elliott & Lowitz, 2019). For the 2020 cohort, the baseline year is measured in February 2020, year 1 is February 2021, year 2 is February 2022, and year 3 is August 2023. For the 2016 cohort, the baseline year is measured in August 2016, year 1 is August 2017, year 2 is August 2018, and year 3 is August 2019. Consumer age is measured in the baseline year and follows the same consumers over time, such that each cohort is non-overlapping as consumers are considered members of the cohort if they are within the three-year age range in the baseline year. All estimates are weighted using weights from the exact matching process.

Table 4: Community-Level Racial Disparities Widen or Stay the Same for the 2016 Cohort But Decrease for the 2020 Cohort

Community-Level Racial Disparities in Average Credit Scores by Cohort and Over Time Between Young Adults Living in Communities of Color and Majority White Communities in the Matched Sample

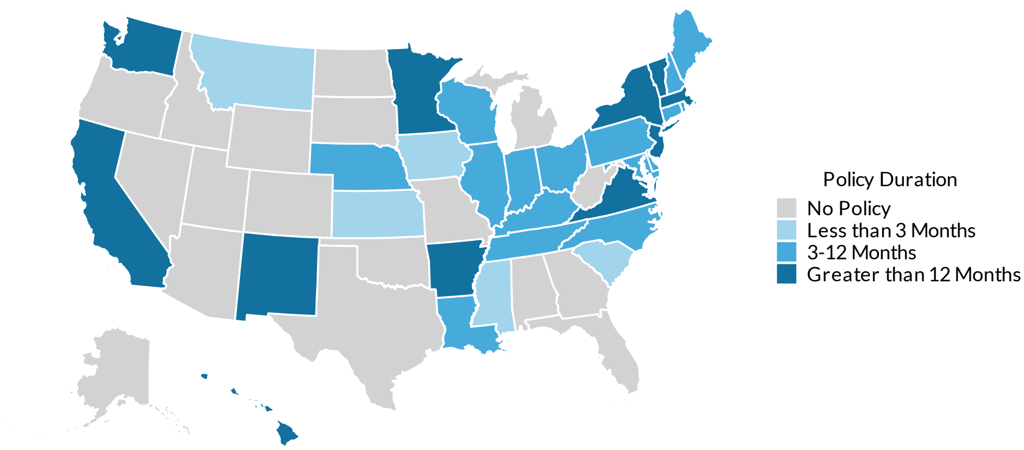
	Baseline	**1 Year**	**2 Years**	**3 Years**
MAJORITY BLACK COMMUNITIES				
Young Adults Ages 20-23				
2016 Cohort	70.3	77.0***	78.8***	80.2***
2020 Cohort	61.7	59.1***	60.3**	60.9
Young Adults Ages 24-26				
2016 Cohort	74.5	77.1***	76.9***	77.4***
2020 Cohort	70.0	63.9***	64.3***	62.6***
Young Adults Ages 27-29				
2016 Cohort	76.1	77.3**	78.5***	78.0***
2020 Cohort	68.1	63.0***	62.0***	61.1***
MAJORITY LATINX COMMUNITIES				
Young Adults Ages 20-23				
2016 Cohort	32.8	36.0***	36.1***	37.1***
2020 Cohort	30.3	28.0***	28.9***	32.5***
Young Adults Ages 24-26				
2016 Cohort	38.3	38.5	37.7	38.0
2020 Cohort	34.7	31.1***	31.1***	33.4**
Young Adults Ages 27-29				
2016 Cohort	38.2	38.5	38.6	38.6
2020 Cohort	34.7	31.5***	30.4***	33.2***
MAJORITY NATIVE COMMUNITIES				
Young Adults Ages 20-23				
2016 Cohort	75.2	79.1	75.5	74.7
2020 Cohort	67.2	64.8	64.8	69.5
Young Adults Ages 24-26				
2016 Cohort	88.5	91.7	92.7	91.9
2020 Cohort	75.8	77.8	73.8	69.3
Young Adults Ages 27-29				
2016 Cohort	91.1	91.8	93.8	91.4
2020 Cohort	83.0	79.2**		79.4

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows the regression output of the average difference in weighted credit scores over a three-year period between young adults living in communities of color and majority White communities by cohort and year. Majority Black, Latinx, White, and Native American communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. The sample includes consumers with a credit bureau record that are similar in age and baseline credit scores across cohorts. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the p<0.01 level, ** denotes that the coefficient estimate is statistically significant at the p<0.05 level, and * denotes that the coefficient estimate is statistically significant at the p<0.10 level. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be unlikely to be approved for new credit (Elliott & Lowitz, 2019). For the 2020 cohort, the baseline year is measured in February 2020, year 1 is February 2021, year 2 is February 2022, and year 3 is August 2023. For the 2016 cohort, the baseline year is measured in August 2016, year

1 is August 2017, year 2 is August 2018, and year 3 is August 2019. Consumer age is measured in the baseline year and follows the same consumers over time, such that each cohort is non-overlapping as consumers are considered members of the cohort if they are within the three-year age range in the baseline year. All estimates are weighted using weights from the exact matching process.

Figure 8: Some States Implemented Utility Shutoff Moratoria during the Pandemic

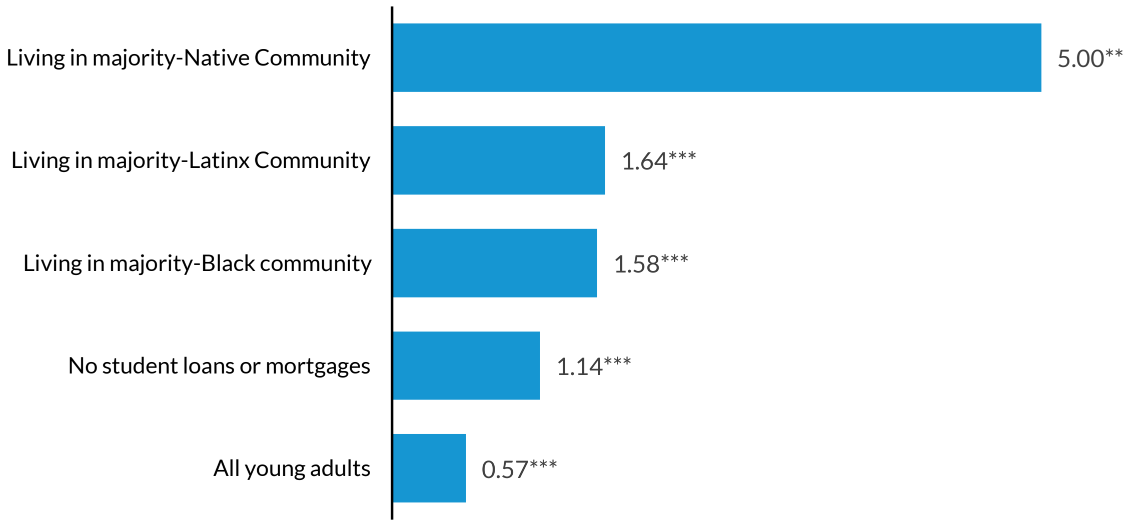
States that implemented utility shutoff moratoria, by policy duration



Sources: COVID-19 Eviction Moratoria and Housing Policy dataset (2023), as shown in Andre et al. (2023, 2024).
Notes: This map shows in gradations of blue states that implemented utility shutoff moratoria between February 2020 and August 2023, by the length of time the policy was active. Darker blue shades identify states that had utility shutoff moratoria in place over longer periods.

Figure 9: Utility Shutoff Moratoria Marginally Increased Young Adults' Credit Scores

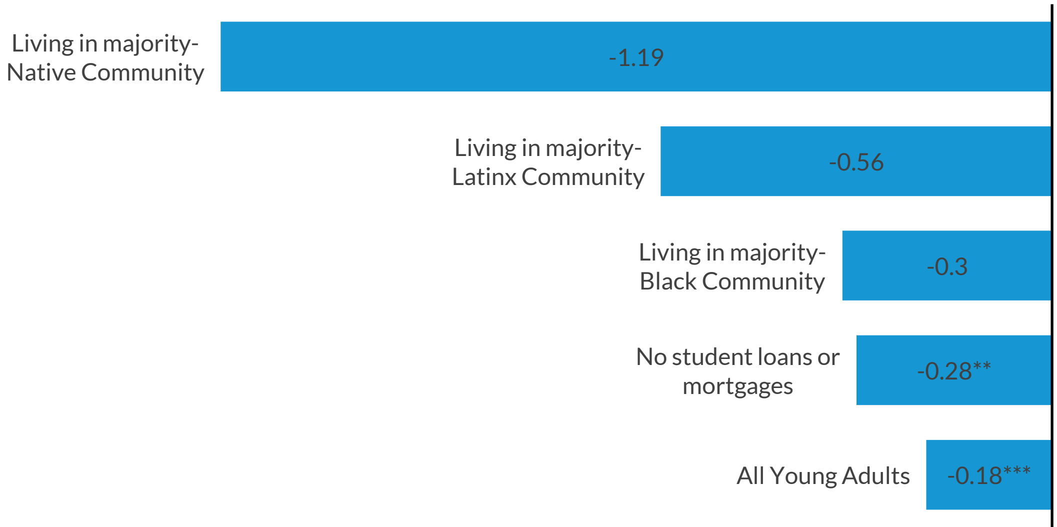
Changes in young adults' (ages 20 to 29) average credit scores (in points) after implementation of state-level utility shutoff moratoria, across different groups



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays difference-in-difference estimates of the impact of state-level utility shutoff moratoria on consumer VantageScore credit scores for young adults ages 20 to 29 with a credit bureau record (full regression tables shown in tables B.3 and B.4). Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level.

Figure 10: Utility Shutoff Moratoria Reduced Young Adults' Delinquencies

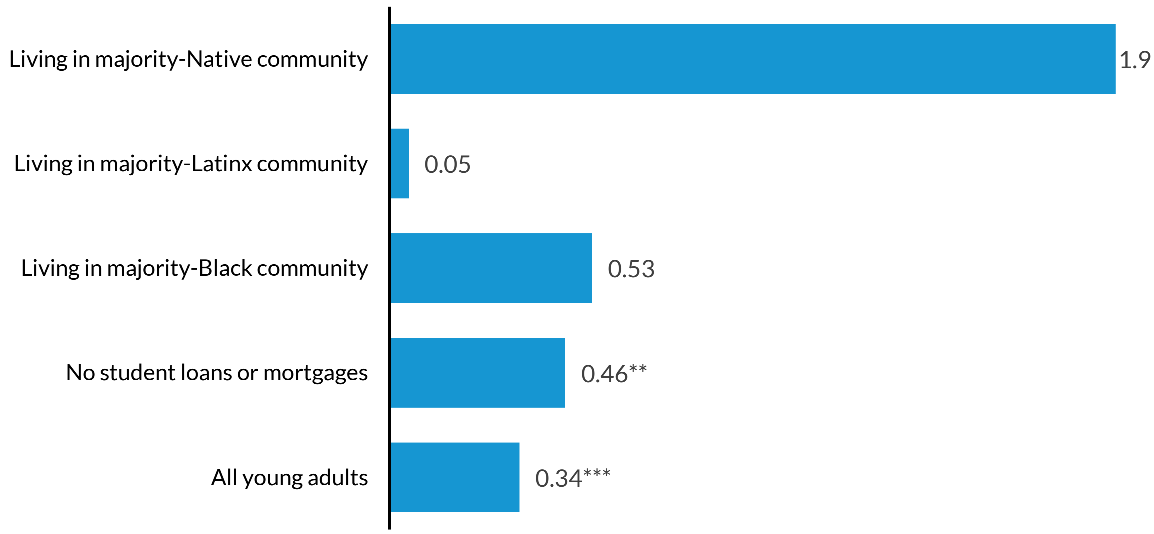
Percentage point changes in the share of young adults (ages 20 to 29) with a 30+ day late credit card bill after implementation of state-level utility shutoff moratoria, across different groups



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays difference-in-difference estimates of the impact of state-level utility shutoff moratoria on the share of young adults ages 20 to 29 with a credit bureau record and a 30+ day late credit card payment (full regression tables shown in tables B.5 and B.6). Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level.

Figure 11: Longer Extended UI Programs (20 Week) Marginally Increased Young Adults' Credit Scores

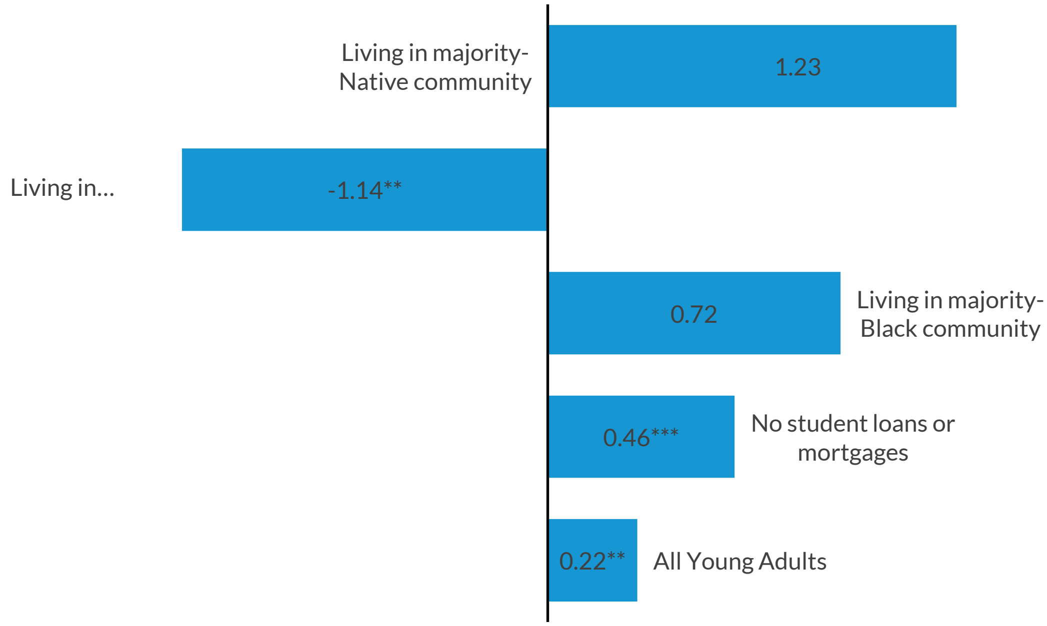
Changes in young adults' (ages 20 to 29) average credit scores (in points) after implementation of state-level 20-week extended benefits UI programs, across different groups



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays difference-in-difference estimates of the impact of state-level 20-week extended UI programs on consumer credit scores for young adults ages 20 to 29 with a credit bureau record (full regression tables shown in tables B.3 and B.4). Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level.

Figure 12: Extended UI Programs (13 Week) May Marginally Improve Credit Scores of Young Adults Living in Majority-Black Communities

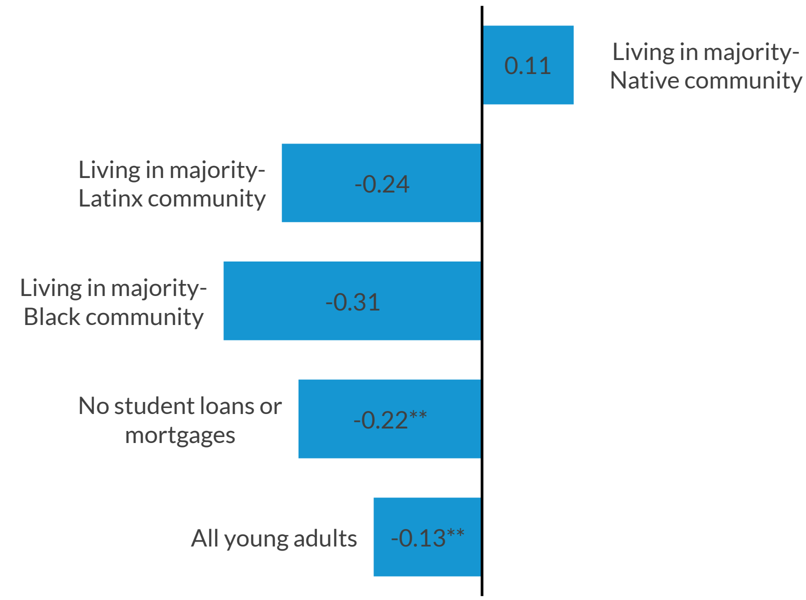
Changes in young adults' (ages 20 to 29) average credit scores (in points) after implementation of state-level 13-week extended benefits UI programs, across different groups



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays difference-in-difference estimates of the impact of state-level 13-week extended UI programs on consumer credit scores for young adults ages 20 to 29 with a credit bureau record (full regression tables shown in tables B.3 and B.4). Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level.

Figure 13: Longer Extended UI Programs (20 Week) Decreased Young Adults' Delinquencies

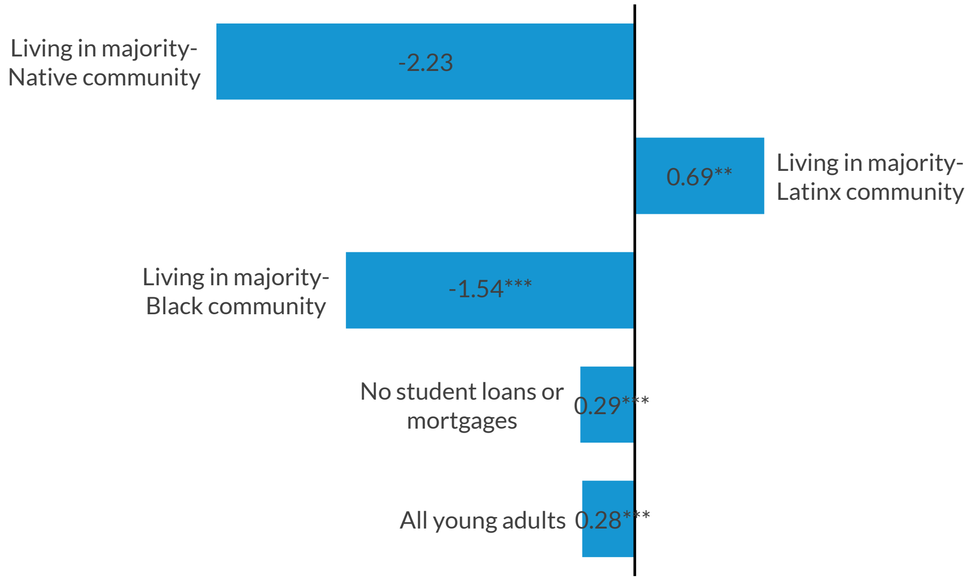
Percentage point changes in the share of young adults (ages 20 to 29) with a 30+ day late credit card bill after implementation of state-level 20-week extended benefits UI programs, across different groups



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays difference-in-difference estimates of the impact of state-level 20-week extended UI programs on the share of young adults ages 20 to 29 with a credit bureau record and a 30+ day late credit card payment (full regression tables shown in tables B.5 and B.6). Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level.

Figure 14: Extended UI Programs (13-week) Decreased Delinquencies for Young Adults Living 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



Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: The figure displays difference-in-difference estimates of the impact of state-level 13-week extended UI programs on the share of young adults ages 20 to 29 with a credit bureau record and a 30+ day late credit card payment (full regression tables shown in tables B.5 and B.6). Young adults are classified as living in a majority-Black or majority-Latinx community if they live in Zip Code Tabulation Areas where more than 50 percent of the population identifies as a particular race or ethnicity in the 2015–19 five-year American Community Survey in February 2020. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level.

Appendix A. Additional Data Details

Table A.1: Share of Sample in Each Age in February 2020

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

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows the share of consumers from the baseline period in February 2020 that are each age.

Table A.2: Loan Use and Credit Scores of the Analytic Sample (Young Adults Ages 20-29) in February 2020

Indicator	Value
Average Credit Score	642.1
Share with Subprime Credit	33.7
Share with a Student Loan	33.9
Share with a Credit Card	55.1
Share with an Auto Loan	36.6
Share with an AFS Loan	4.5
Share with a Mortgage	7.6

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows the baseline characteristics of the analytic sample overall, including loan use and credit profiles. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). In this data, consumers are flagged as using alternative financial services loans if they use 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.

Table A.3: Share of Sample (Young Adults Ages 20-29) Living in Each Community in February 2020

Community	Share of Consumers Living in this Community	Number of Consumers Living in this Community
Majority Black Community	6.12	4,9352
Majority Latinx Community	11.53	92,965
Majority Native American Community	0.14	1,156

Majority White Community	63.91	515,423

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows the share of consumers from the baseline period in February 2020 that live in each community. Majority Black, Latinx, Native American, and White communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey.

Table A.4: Loan Use and Credit Scores of the Analytic Sample (Young Adults Ages 20-29) in February 2020, by Community Composition

Indicator	Majority Black	Majority Latinx	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

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows the baseline characteristics of the analytic sample overall, including loan use and credit profiles. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). In this data, consumers are flagged as using alternative financial services loans if they use 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. Majority Black, Latinx, Native American, and White communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey.

Table A.5: Missing Data in Age-Specific American Community Survey Variables for Young Adults Ages 20-29 at the ZCTA Level

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

Source: American Community Survey (2015-2019)
Notes: Median income: Median income over the past 12 months for adults ages 15-24, 25-44 in the ZCTA. Educational attainment: The share of ZCTA residents with a bachelor's degree or higher for adults ages 18-24, 25-34. Employment status: The share of ZCTA residents with employment for adults ages 20-24, 24-29.

Table A.6: Missing Data in Age-Specific American Community Survey Variables for Young Adults Ages 20-29 at the Consumer Level

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

Source: American Community Survey (2015-2019)
Notes: Median income: Median income over the past 12 months for adults ages 15-24, 25-44 in the ZCTA. Educational attainment: The share of ZCTA residents with a bachelor's degree or higher for adults ages 18-24, 25-34. Employment status: The share of ZCTA residents with employment for adults ages 20-24, 24-29. Data for mortgage holding has no missing values.

Table A.7: Description of Oaxaca-Blinder Decomposition Coefficients

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.
Constant	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)." (Etezady et al 2020).

Source: Author's analysis, adapted from Rahimi & Hashemi Nazari (2021) and Etezady et al (2020).
Notes: These descriptions apply to a three-way Oaxaca-Blinder decomposition.

Table A.8: Number of Observations in the Matched and Unmatched Cohorts

	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

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows the share and number of consumers present in the matched and unmatched samples, by age group.

Table A.9: Mean Credit Scores in the Matched and Unmatched Cohorts Over Time

	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

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows the average credit scores of the matched and unmatched samples over time for young adults ages 20-23, 24-26, and 27-29. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019).

Appendix B: Additional Results

Table B.1: Oaxaca-Blinder Decomposition on Imputed and Non-Imputed ACS Data, Majority Black Communities

	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

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows output from a three-way Oaxaca-Blinder decomposition, which decomposes the difference in mean credit scores between young adults living in majority White and majority Black communities. The covariates included in the model are age-specific rates of employment, mortgage ownership, income, and educational attainment, measured at the ZCTA level in the 5-year 2015-2019 American Community Survey. Majority White communities are the reference group. Majority Black, Latinx, White, and Native American communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). Differences in means are measured in points. See Table 4.2 for a breakdown of the meaning of each coefficient presented in this table.

Table B.2: Oaxaca-Blinder Decomposition on Imputed and Non-Imputed ACS Data, Majority Latinx Communities

	Non-Imputed	**Imputed**
Mean Credit Score for Majority White Communities	652.1405	652.2485
Mean Credit Score for Majority Latinx 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

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows output from a three-way Oaxaca-Blinder decomposition, which decomposes the difference in mean credit scores between young adults living in majority White and majority Latinx communities. The covariates included in the model are age-specific rates of employment, mortgage ownership, income, and educational attainment, measured at the ZCTA level in the 5-year 2015-2019 American Community Survey. Majority White communities are the reference group. Majority Black, Latinx, White, and Native American communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). Differences in means are measured in points. See Table 4.2 for a breakdown of the meaning of each coefficient presented in this table.

Table B.3: Oaxaca-Blinder Decomposition on Imputed and Non-Imputed ACS Data, Majority Native Communities

	Non-Imputed	**Imputed**
Mean Credit Score for Majority White Communities	652.1405	652.2485
Mean Credit Score for Majority Native 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

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows output from a three-way Oaxaca-Blinder decomposition, which decomposes the difference in mean credit scores between young adults living in majority White and majority Native communities. The covariates included in the model are age-specific rates of employment, mortgage ownership, income, and educational attainment, measured at the ZCTA level in the 5-year 2015-2019 American Community Survey. Majority White communities are the reference group. Majority Black, Latinx, White, and Native American communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). Differences in means are measured in points. See Table 4.2 for a breakdown of the meaning of each coefficient presented in this table.

Table B.4: Young Adults See Gains in Credit Scores over the Pandemic and Declines in Community-Level Racial Disparities

Trends in average credit scores and community-level racial disparities in credit scores from February 2020 to August 2023 among young adults (20 to 29)

	(1)	(2)	(3)	(4)
VARIABLES	1: Time Only	2: Black	3: Latinx	4: Native
TIME TREND				
Time Period = 1, 2018	-5.03775	-5.79428	-5.79428	-5.79428
	(0.08778)***	(0.10244)***	(0.10244)***	(0.10244)***
Time Period = 2, 2019	-2.14134	-2.40128	-2.40128	-2.40128
	(0.06008)***	(0.07061)***	(0.07061)***	(0.07061)***
Time Period = 4, 04/2020	6.07390	5.84638	5.84638	5.84638
	(0.03745)***	(0.04506)***	(0.04506)***	(0.04506)***
Time Period = 5, 06/2020	9.97624	9.35325	9.35325	9.35325
	(0.04716)***	(0.05470)***	(0.05470)***	(0.05470)***
Time Period = 6, 08/2020	11.21785	10.23483	10.23483	10.23483
	(0.05513)***	(0.06157)***	(0.06157)***	(0.06157)***
Time Period = 7, 10/2020	11.93988	10.84404	10.84404	10.84404
	(0.06100)***	(0.06836)***	(0.06836)***	(0.06836)***
Time Period = 8, 12/2020	11.69657	10.58043	10.58043	10.58043
	(0.06434)***	(0.07265)***	(0.07265)***	(0.07265)***
Time Period = 9, 02/2021	14.54690	13.43168	13.43168	13.43168
	(0.06838)***	(0.07671)***	(0.07671)***	(0.07671)***
Time Period = 10, 08/2021	18.84611	17.33888	17.33888	17.33888
	(0.08202)***	(0.09128)***	(0.09128)***	(0.09128)***
Time Period = 11, 02/2022	20.01283	18.91256	18.91256	18.91256
	(0.08563)***	(0.09940)***	(0.09940)***	(0.09940)***
Time Period = 12, 08/2022	20.46209	19.61370	19.61370	19.61370
	(0.09206)***	(0.10761)***	(0.10761)***	(0.10761)***
Time Period = 13, 08/2023	26.35322	25.94811	25.94811	25.94811
	(0.11289)***	(0.13047)***	(0.13047)***	(0.13047)***
INITIAL DISPARITIES				
Effect of Being in a Community of Color in February 2020		-67.05569	-33.52915	-74.83553
		(1.43406)***	(0.99929)***	(3.05690)***
INTERACTION TERMS: CHANGES IN DISPARITY OVER TIME				
August 2019 Time Interaction with Community of Color		-2.01140	1.62485	-1.44691
		(0.28161)***	(0.20752)***	(1.56606)
April 2020 Time Interaction with Community of Color		0.95757	0.79235	0.14377
		(0.17164)***	(0.12075)***	(1.13040)
June 2020 Time Interaction with Community of Color		1.64105	2.23566	0.05956
		(0.21268)***	(0.15893)***	(1.30869)

August 2020 Time Interaction with Community of Color		3.28804	3.16264	0.97776
		(0.24686)***	(0.18010)***	(1.36837)
October 2020 Time Interaction with Community of Color		3.96352	3.34042	2.12995
		(0.26809)***	(0.20058)***	(1.43515)
December 2020 Time Interaction with Community of Color		4.63529	3.07992	3.11394
		(0.28935)***	(0.21313)***	(1.50301)**
February 2021 Time Interaction with Community of Color		4.83744	3.22443	1.94546
		(0.30822)***	(0.23042)***	(1.50726)
August 2021 Time Interaction with Community of Color		6.64692	4.99999	2.23139
		(0.35596)***	(0.26239)***	(1.76871)
February 2022 Time Interaction with Community of Color		4.63963	3.32098	3.10580
		(0.37837)***	(0.28593)***	(1.99775)
August 2022 Time Interaction with Community of Color		4.16849	2.59968	2.41125
		(0.40281)***	(0.30923)***	(2.18350)
August 2023 Time Interaction with Community of Color		5.27203	0.41496	1.76088
		(0.51303)***	(0.38063)	(2.55062)
Constant	642.14943	652.21940	652.21940	652.21940
	(0.40024)***	(0.41263)***	(0.41263)***	(0.41263)***
Observations	9,703,535	6,839,660	7,362,147	6,281,081
R-squared	0.00840	0.04243	0.02182	0.00963
Mean of Dependent Variable	642.1	646.5	647.2	652.1

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the average difference in credit scores between young adults ages 20 to 29 living in communities of color relative to those living in majority-white communities in February 2020 and changes in this disparity over time. The sample includes consumers with a credit bureau record. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents regression estimates for all consumers, and columns 2 through 4 present estimates for consumers living in communities of color in February 2020. Majority-Black, majority-Latinx, and majority-Native communities are zip codes where more than 50 percent of residents were in the respective racial or ethnic group in the five-year 2015–19 American Community Survey. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott and Lowitz 2019). This table shows descriptive regression results, not impact estimates.

Table B.5: Young Adults See Sharp Increases in Credit Card Delinquencies in 2022 and 2023, with Sharper Gains among Young Adults Living in Majority-Black and Majority-Native Communities

Trends in average credit scores and community-level racial disparities in credit scores from February 2020 to August 2023 among young adults (20 to 29) with a credit card

	(1)	(2)	(3)	(4)
VARIABLES	1: Time Only	2: Black	3: Latinx	4: Native
TIME TREND				
Time Period = 1, 2018	-0.62792	-0.46647	-0.46647	-0.46647
	(0.05558)***	(0.06355)***	(0.06355)***	(0.06355)***
Time Period = 2, 2019	-0.69854	-0.62766	-0.62766	-0.62766
	(0.04233)***	(0.04824)***	(0.04824)***	(0.04824)***
Time Period = 4, 04/2020	-0.66515	-0.61636	-0.61636	-0.61636
	(0.03036)***	(0.03546)***	(0.03546)***	(0.03546)***
Time Period = 5, 06/2020	-1.96086	-1.76083	-1.76083	-1.76083
	(0.03668)***	(0.04173)***	(0.04173)***	(0.04173)***
Time Period = 6, 08/2020	-2.28211	-1.92348	-1.92348	-1.92348
	(0.04123)***	(0.04632)***	(0.04632)***	(0.04632)***
Time Period = 7, 10/2020	-2.55814	-2.10206	-2.10206	-2.10206
	(0.04623)***	(0.05140)***	(0.05140)***	(0.05140)***
Time Period = 8, 12/2020	-2.35201	-1.89533	-1.89533	-1.89533
	(0.04924)***	(0.05498)***	(0.05498)***	(0.05498)***
Time Period = 9, 02/2021	-2.56766	-2.11695	-2.11695	-2.11695
	(0.05070)***	(0.05630)***	(0.05630)***	(0.05630)***
Time Period = 10, 08/2021	-2.86935	-2.38696	-2.38696	-2.38696
	(0.05197)***	(0.05798)***	(0.05798)***	(0.05798)***
Time Period = 11, 02/2022	-0.97614	-0.80682	-0.80682	-0.80682
	(0.05263)***	(0.05993)***	(0.05993)***	(0.05993)***
Time Period = 12, 08/2022	0.16822	0.08528	0.08528	0.08528
	(0.05361)***	(0.06153)	(0.06153)	(0.06153)
Time Period = 13, 08/2023	1.46617	1.15626	1.15626	1.15626
	(0.05564)***	(0.06289)***	(0.06289)***	(0.06289)***
INITIAL DISPARITIES				
Effect of Being in a Community of Color in February 2020		9.55589	4.07457	6.67828
		(0.37051)***	(0.18347)***	(2.18569)***
INTERACTION TERMS: CHANGES IN DISPARITY OVER TIME				
August 2019 Time Interaction with Community of Color		-0.62082	-0.27732	-2.29172
		(0.27610)**	(0.16125)*	(2.30655)
April 2020 Time Interaction with Community of Color		-1.10850	-0.22706	-1.44713
		(0.19714)***	(0.10408)**	(1.77301)
June 2020 Time Interaction with Community of Color		-2.69938	-0.72655	-3.36470

		(0.24901)***	(0.12948)***	(1.64842)**
August 2020 Time Interaction with Community of Color		-3.62826	-1.27625	-4.33967
		(0.27903)***	(0.14759)***	(1.81101)**
October 2020 Time Interaction with Community of Color		-4.02659	-1.66504	-1.42832
		(0.30237)***	(0.16369)***	(2.02710)
December 2020 Time Interaction with Community of Color		-3.46119	-1.82026	-1.96710
		(0.33015)***	(0.17465)***	(2.39678)
February 2021 Time Interaction with Community of Color		-3.23144	-1.89656	-1.98883
		(0.33660)***	(0.18129)***	(2.40421)
August 2021 Time Interaction with Community of Color		-3.35366	-2.15081	-0.97439
		(0.34945)***	(0.18035)***	(2.20842)
February 2022 Time Interaction with Community of Color		0.19916	-1.62407	-2.47503
		(0.35046)	(0.18860)***	(2.36223)
August 2022 Time Interaction with Community of Color		2.03046	-0.66699	-1.73162
		(0.34866)***	(0.19358)***	(2.56471)
August 2023 Time Interaction with Community of Color		2.56294	0.43293	3.12945
		(0.35997)***	(0.20096)**	(2.70567)
Constant	7.97259	6.81378	6.81378	6.81378
	(0.05776)***	(0.05913)***	(0.05913)***	(0.05913)***
Observations	5,852,204	4,129,908	4,488,003	3,875,714
R-squared	0.00270	0.00979	0.00442	0.00216
Mean of Dependent Variable	7.973	7.385	7.376	6.820

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the average difference in the share of consumers with credit card delinquencies between young adults ages 20 to 29 living in communities of color and those living in majority-white communities in February 2020 and changes in this disparity over time. The sample includes consumers with a credit bureau record and at least one credit card. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents regression estimates for all consumers, and columns 2 through 4 present estimates for consumers living in communities of color in February 2020. Majority-Black, majority-Latinx, and majority-Native communities are zip codes where more than 50 percent of residents were in the respective racial or ethnic group in the five-year 2015–19 American Community Survey. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card. This table shows descriptive regression results, not impact estimates.

Table B.6: Oaxaca-Blinder (OB) Decomposition for Majority Native Communities Relative to Majority White Communities

	Coefficient	Robust Standard Error	z	P>|z|	[95% conf.	interval]
OVERALL						
Mean Credit Score for Majority White Communities	652.249	0.13882	4698.48	0	651.976	652.521
Mean Credit Score for Majority Black Communities	577.211	2.57401	224.25	0	572.166	582.256
Difference in Means	75.0375	2.57775	29.11	0	69.9852	80.0898
Difference in Means Due to Endowments	36.7736	0.72716	50.57	0	35.3484	38.1988
Difference in Means Due to Coefficients	52.1386	9.29995	5.61	0	33.9111	70.3662
Difference in Means Due to Interactions	-13.875	8.76797	-1.58	0.114	-31.06	3.31024
ENDOWMENT EFFECTS BY COVARIATE						
Median Household Income	2.62457	0.15699	16.72	0	2.31687	2.93227
Share with a Bachelors Degree or Higher	19.3252	0.2775	69.64	0	18.7813	19.8691
Share Employed	-6.8326	0.33745	-20.25	0	-7.494	-6.1712
Share with a Mortgage	21.6565	0.66497	32.57	0	20.3531	22.9598
COEFFICIENT EFFECTS BY COVARIATE						
Median Household Income	-7.2199	8.72936	-0.83	0.408	-24.329	9.88934
Share with a Bachelors Degree or Higher	25.9532	11.4157	2.27	0.023	3.57882	48.3275
Share Employed	-41.293	12.9271	-3.19	0.001	-66.629	-15.956
Share with a Mortgage	10.4908	8.32063	1.26	0.207	-5.8173	26.799
_cons	64.207	10.2032	6.29	0	44.2091	84.2049
INTERACTION EFFECTS BY COVARIATE						
Median Household Income	2.83201	3.42474	0.83	0.408	-3.8804	9.54438

Share with a Bachelors Degree or Higher	-20.37	8.96262	-2.27	0.023	-37.937	-2.804
Share Employed	10.4116	3.27091	3.18	0.001	4.00075	16.8225
Share with a Mortgage	-6.7479	5.35307	-1.26	0.207	-17.24	3.74397

Source: Author's analysis of Urban Institute credit bureau data, as published in Martinchek (2024a).
Notes: This table shows output from a three-way Oaxaca-Blinder decomposition, which decomposes the difference in mean credit scores between young adults living in majority White and majority Native communities. The covariates included in the model are age-specific rates of employment, mortgage ownership, income, and educational attainment, measured at the ZCTA-level in the 5-year 2015-2019 American Community Survey. Majority White communities are the reference group. Majority Black, Latinx, White, and Native communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the 5-year 2015-2019 American Community Survey. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record. In VantageScore, credit scores below 600 are considered subprime and often signal that consumers may face higher costs in borrowing and be likely to be approved for new credit (Elliott & Lowitz, 2019). Difference in means are measured in points. See Table 4.2 for a breakdown of the meaning of each coefficient presented in this table.

Table B.7: Difference-in-Difference Impact Estimates for Credit Scores

Point change in young adults' (ages 20 to 29) average credit scores post-policy

Model	(1)	(2)	(3)	(4)	(5)
Description	**County FEs**	**County FEs with controls**	**Individual FEs**	**Individual FEs with controls**	**Individual FEs with controls, no students**
Policy impacts					
Utility moratoria	1.07221	0.75227	0.87667	0.57175	1.13931
	(0.10729)***	(0.09634)***	(0.10097)***	(0.08909)***	(0.16744)***
Extended UI	0.30331	0.14220	0.37743	0.22128	0.45931
	(0.11681)***	(0.10797)	(0.10806)***	(0.10149)**	(0.15987)***
Extended UI 20 wks	0.76363	0.34615	0.72029	0.34200	0.45715
	(0.09329)***	(0.09707)***	(0.08764)***	(0.09031)***	(0.17254)***
Controls	No	Yes	No	Yes	Yes
Fixed effects	County and time		Individual and time		
Observations	9,702,581	9,702,581	9,702,581	9,702,581	1,979,598
R-squared	0.07382	0.07422	0.85795	0.85798	0.81686
Mean of dependent variable	642.2	642.2	642.2	642.2	639.6

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis. The sample includes consumers with a credit bureau record. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Column 5 presents estimates using individual and time fixed effects and controls for a subsample of consumers without student loans or mortgage loans in February 2020. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossession suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic

Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the COVID-19 US State Policy Database. Fixed effects (FEs) control for all factors (observed and unobserved) that remain constant within units (individual consumers or counties) and periods. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.8: Difference-in-Difference Impact Estimates for Credit Scores, by Community Composition

Point change in young adults' (ages 20 to 29) average credit score post-policy

Model	**(3)**	**(5)**	**(7)**
Description	**Majority-Native**	**Majority-Black**	**Majority-Latinx**
Policy impacts			
Utility moratoria	4.960989	1.57766	1.63818
	(2.350242)**	(0.60016)***	(0.52959)***
Extended UI	1.230329	0.71881	-1.13596
	(2.040479)	(0.48762)	(0.55406)**
Extended UI 20 wks	1.878365	0.52961	0.05078
	(1.550399)	(0.56745)	(0.33696)
Controls		Yes	
Fixed effects		Individual and time	
Observations	5,488	175,509	432,273
R-squared	0.76494	0.79223	0.80107
Mean of dependent variable	589.8	600.8	627.4

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis. The sample includes consumers with a credit bureau record. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents regression estimates for all consumers, and columns 2 through 4 present estimates for consumers living in communities of color in February 2020. All estimates include individual and time fixed effects and controls. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Majority-Black, majority-Latinx, and majority-Native communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the five-year 2015–19 American Community Survey. Consumers are defined as living in communities of color if their address of residence in February 2020 is in a ZIP Code Tabulation Area that meets the criteria. Fixed effects (FEs) control for all factors (observed and unobserved) that remain constant within units (individual consumers or counties) and periods. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.9: Difference-in-Difference Impact Estimates for Credit Card Delinquencies

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card payment post-policy

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Description	**County FEs**	**County FEs with controls**	**Individual FEs**	**Individual FEs with controls**	**Individual FEs with controls, no students**
Policy impacts					
Utility moratoria	-0.20922	-0.24177	-0.11861	-0.17842	-0.27909
	(0.06740)***	(0.06475)***	(0.05797)**	(0.05402)***	(0.11370)**
Extended UI	-0.26523	-0.28460	-0.25630	-0.27885	-0.29317
	(0.06146)***	(0.05915)***	(0.04773)***	(0.04756)***	(0.10562)***
Extended UI 20 wks	-0.04680	-0.06647	-0.10239	-0.12535	-0.22307
	(0.06910)	(0.07034)	(0.05517)*	(0.05787)**	(0.10937)**
Controls	No	Yes	No	Yes	Yes
Fixed effects	County and time		Individual and time		
Observations	5,851,910	5,851,910	5,851,910	5,851,910	1,282,308
R-squared	0.01119	0.01127	0.46696	0.46701	0.44399
Mean of dependent variable	7.973	7.973	7.973	7.973	10.50

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis. The sample includes consumers with a credit bureau record and at least one credit card. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Column 5 presents estimates using individual and time fixed effects and controls for a subsample of consumers without student loans or mortgage loans in February 2020. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Fixed effects (FEs) control for all factors (observed and unobserved) that remain constant within units (individual consumers or counties) and periods. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

Tabel B.10: Difference-in-Difference Impact Estimates for Credit Card Delinquencies by Community Composition

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card payment post-policy

Model	**(3)**	**(5)**	**(7)**
Description	**Majority-Native**	**Majority-Black**	**Majority-Latinx**
Policy impacts			
Utility moratoria	-1.190235	-0.29816	-0.55839
	(3.266284)	(0.47757)	(0.37606)
Extended UI	-2.227844	-1.54354	0.68858
	(1.825539)	(0.42003)***	(0.29417)**
Extended UI 20 wks	0.110408	-0.30658	-0.23889
	(1.712172)	(0.47261)	(0.24489)
Controls		Yes	
Fixed effects		Individual and time	
Observations	1,879	109,732	290,035
R-squared	0.48559	0.42708	0.43245
Mean of dependent variable	11.76	16.90	12.22

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis. The sample includes consumers with a credit bureau record and at least one credit card. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents regression estimates for all consumers, and columns 2 through 4 present estimates for consumers living in communities of color in February 2020. All estimates include individual and time fixed effects and controls. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Majority-Black, majority-Latinx, and majority-Native communities are zip codes where more than 50 percent of residents are in the respective racial or ethnic group in the five-year 2015–19 American Community Survey. Consumers are defined as living in communities of color if their address of residence in February 2020 is in a ZIP Code Tabulation Area that meets the criteria. Fixed effects (FEs) control for all factors (observed and unobserved) that remain constant within units (individual consumers or counties) and periods. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

Table B.11: Contiguous County Policy Impact Estimates for Utility Shutoff Moratoria on Credit Scores

Point change in young adults' (ages 20 to 29) average credit scores post-policy

Model	**(2)**	**(4)**	**(6)**
Description	**County fixed effects**	**Pair-time fixed effects**	**Pair-time and county fixed effects**

Policy impact			
Utility moratoria	0.75672 (0.18775)***	-0.04146 (1.78803)	0.20619 (0.21843)
Controls		Yes	
Fixed effects	County	Pair-time	County and pair-time
Observations	38,814	38,810	38,810
R-squared	0.98733	0.87891	0.99507
Mean of dependent variable	630	630	630

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the contiguous county policy impact analysis. The sample includes consumers with a credit bureau record. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county fixed effects and controls. Column 2 presents estimates pair-time fixed effects and controls. Column 3 presents estimates using pair-time and county fixed effects and controls. Model 6 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional unemployment insurance allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.12: Policy Impact Estimates for Utility Shutoff Moratoria on Credit Scores among Consumers in Contiguous Counties

Point change in young adults' (ages 20 to 29) average credit scores post-policy

Model	(1)	(2)	(3)	(4)
Description	**County FEs**	**County FEs with controls**	**Individual FEs**	**Individual FEs with controls**
Policy impacts				
Utility moratoria	1.03690 (0.17090)***	0.74467 (0.16098)***	0.87846 (0.16073)***	0.61721 (0.14999)***
Controls	No	Yes	No	Yes
Fixed effects	County and time		Individual and time	
Observations	9,702,581	9,702,581	9,702,581	9,702,581
R-squared	0.07382	0.07422	0.85795	0.85798
Mean of dependent variable	642.2	642.2	642.2	642.2

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis on consumers living in bordering counties. The sample includes consumers with a credit bureau record and identifies consumers living in bordering counties within states that implemented utility shutoff moratoria or extended benefits programs (separately) and their neighboring counties within states that never implemented that policy using data from the 1991 Census Bureau Contiguous County File. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the

coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.13: Contiguous County Policy Impact Estimates for Utility Shutoff Moratoria on Credit Card Delinquencies

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card post-policy

Model	(2)	(4)	(6)
Description	**County fixed effects**	**Pair-time fixed effects**	**Pair-time and county fixed effects**
Policy impact			
Utility moratoria	-0.28577 (0.12078)**	-0.07027 (0.20448)	-0.28071 (0.14569)*
Controls		Yes	
Fixed effects	County	Pair-time	County and pair-time
Observations	38,517	38,220	38,218
R-squared	0.59255	0.68899	0.81518
Mean of dependent variable	9.037	9.058	9.058

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the contiguous county policy impact analysis. The sample includes consumers with a credit bureau record and at least one credit card. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county fixed effects and controls. Column 2 presents estimates pair-time fixed effects and controls. Column 3 presents estimates using pair-time and county fixed effects and controls. Model 6 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

Table B.14: Policy Impact Estimates for Utility Shutoff Moratoria on Credit Card Delinquencies among Consumers in Contiguous Counties

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card post-policy

Model	(1)	(2)	(3)	(4)
Description	County FEs	County FEs with controls	Individual FEs	Individual FEs with controls
Policy impacts				
Utility moratoria	-0.20720	-0.28863	-0.15621	-0.22199
	(0.10964)*	(0.10826)***	(0.08207)*	(0.08232)***
Controls	No	Yes	No	Yes
Fixed effects	County and time		Individual and time	
Observations	1,743,359	1,743,359	1,743,359	1,743,359
R-squared	0.01114	0.01117	0.46977	0.46981
Mean of dependent variable	7.870	7.870	7.870	7.870

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis on consumers living in bordering counties. The sample includes consumers with a credit bureau record, an open credit card, and identifies consumers living in bordering counties within states that implemented utility shutoff moratoria or extended benefits programs (separately) and their neighboring counties within states that never implemented that policy using data from the 1991 Census Bureau Contiguous County File. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional unemployment insurance allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

Table B.15: Contiguous County Policy Impact Estimates for 13-Week Extended UI Programs on Credit Scores [PROVISIONAL RESULTS]

Point change in young adults' (ages 20 to 29) average credit scores post-policy

Model	(2)	(4)	(6)
Description	County fixed effects	Pair-time fixed effects	Pair-time and county fixed effects
Policy impact			
Extended UI	0.10232	-0.11992	0.19012
	(0.20198)	(1.76641)	(0.26635)

Controls		Yes	
Fixed effects	County	Pair-time	County and pair-time
Observations	59,988	59,968	59,968
R-squared	0.98675	0.88156	0.99478
Mean of dependent variable	627.9	627.9	627.9

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the contiguous county policy impact analysis. The sample includes consumers with a credit bureau record. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county fixed effects and controls. Column 2 presents estimates pair-time fixed effects and controls. Column 3 presents estimates using pair-time and county fixed effects and controls. Model 6 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional unemployment insurance allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.16: Contiguous County Policy Impact Estimates for 20-Week Extended UI Programs on Credit Scores [PROVISIONAL RESULTS]

Point change in young adults' (ages 20 to 29) average credit scores post-policy

Model	**(2)**	**(4)**	**(6)**
Description	**County fixed effects**	**Pair-time fixed effects**	**Pair-time and county fixed effects**
Policy impact			
Extended UI 20 wks	0.23734	2.52658	-0.03990
	(0.18863)	(1.90374)	(0.25686)
Controls		Yes	
Fixed effects	County	Pair-time	County and pair-time
Observations	25,916	25,910	25,910
R-squared	0.98733	0.89126	0.99511
Mean of dependent variable	629.2	629.2	629.2

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the contiguous county policy impact analysis. The sample includes consumers with a credit bureau record. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county fixed effects and controls. Column 2 presents estimates pair-time fixed effects and controls. Column 3 presents estimates using pair-time and county fixed effects and controls. Model 6 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional unemployment insurance allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US

State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.17: Policy Impact Estimates for 13-Week Extended Benefits UI Programs on Credit Scores among Consumers in Contiguous Counties [PROVISIONAL RESULTS]

Point change in young adults' (ages 20 to 29) average credit scores post-policy

Model	(1)	(2)	(3)	(4)
Description	**County FEs**	**County FEs with controls**	**Individual FEs**	**Individual FEs with controls**
Policy impacts				
Extended UI	0.31890	0.11813	0.44027	0.25561
	(0.21564)	(0.18414)	(0.19672)**	(0.16195)
Controls	No	Yes	No	Yes
Fixed effects	County and Time		Individual and Time	
Observations	3,090,808	3,090,808	3,090,808	3,090,808
R-squared	0.07874	0.07877	0.85954	0.85956
Mean of dependent variable	642	642	642	642

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis on consumers living in bordering counties. The sample includes consumers with a credit bureau record and identifies consumers living in bordering counties within states that implemented utility shutoff moratoria or extended benefits programs (separately) and their neighboring counties within states that never implemented that policy using data from the 1991 Census Bureau Contiguous County File. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.18: Policy Impact Estimates for 20-Week Extended Benefits UI Programs on Credit Scores among Consumers in Contiguous Counties [PROVISIONAL RESULTS]

Point change in young adults' (ages 20 to 29) average credit scores post-policy

Model	(1)	(2)	(3)	(4)
Description	**County FEs**	**County FEs with controls**	**Individual FEs**	**Individual FEs with controls**

Policy impacts				
Extended UI 20 wks	0.41181 (0.16595)**	0.24904 (0.14853)*	0.44685 (0.15548)***	0.29950 (0.14672)**
Controls	No	Yes	No	Yes
Fixed effects	County and time		Individual and time	
Observations	2,564,456	2,564,456	2,564,456	2,564,456
R-squared	0.07469	0.07472	0.85980	0.85983
Mean of dependent variable	643	643	643	643

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis on consumers living in bordering counties. The sample includes consumers with a credit bureau record and identifies consumers living in bordering counties within states that implemented utility shutoff moratoria or extended benefits programs (separately) and their neighboring counties within states that never implemented that policy using data from the 1991 Census Bureau Contiguous County File. Differences in average credit scores are measured in points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. Credit score measures the average VantageScore from 300 to 850 of consumers with a credit bureau record.

Table B.19: Contiguous County Policy Impact Estimates for 13-Week Extended UI Programs on Credit Card Delinquencies [PROVISIONAL RESULTS]

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card post-policy

Model	(2)	(4)	(6)
Description	**County fixed effects**	**Pair-time fixed effects**	**Pair-time and county fixed effects**
Policy impact			
Extended UI	-0.36618 (0.09521)***	-0.17710 (0.22745)	-0.17345 (0.12682)
Controls		Yes	
Fixed effects	County	Pair-time	County and pair-time
Observations	59,304	58,604	58,604
R-squared	0.58275	0.68113	0.80880
Mean of dependent variable	9.220	9.245	9.245

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the contiguous county policy impact analysis. The sample includes consumers with a credit bureau record and at least one credit card. Differences in credit card delinquencies are

measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county fixed effects and controls. Column 2 presents estimates pair-time fixed effects and controls. Column 3 presents estimates using pair-time and county fixed effects and controls. Model 6 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

Table B.20: Contiguous County Policy Impact Estimates for 20-Week Extended UI Programs on Credit Card Delinquencies [PROVISIONAL RESULTS]

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card post-policy

Model	(2)	(4)	(6)
Description	**County fixed effects**	**Pair-time fixed effects**	**Pair-time and county fixed effects**
Policy impact			
Extended UI 20 wks	-0.05407	-0.37782	-0.10010
	(0.10576)	(0.18187)**	(0.13028)
Controls		Yes	
Fixed effects	County	Pair-time	County and pair-time
Observations	25,687	25,454	25,454
R-squared	0.59750	0.70279	0.81843
Mean of dependent variable	8.863	8.885	8.885

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the contiguous county policy impact analysis. The sample includes consumers with a credit bureau record and at least one credit card. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county fixed effects and controls. Column 2 presents estimates pair-time fixed effects and controls. Column 3 presents estimates using pair-time and county fixed effects and controls. Model 6 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

Table B.21: Policy Impact Estimates for 13-Week Extended Benefits UI Programs on Credit Card Delinquencies among Consumers in Contiguous Counties [PROVISIONAL RESULTS]

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card post-policy

Model	**(1)**	**(2)**	**(3)**	**(4)**
Description	**County FEs**	**County FEs with controls**	**Individual FEs**	**Individual FEs with controls**
Policy impacts				
Extended UI	-0.36236	-0.34622	-0.33294	-0.31369
	(0.11834)***	(0.10693)***	(0.10081)***	(0.09402)***
Controls	No	Yes	No	Yes
Fixed effects	County and time		Individual and time	
Observations	1,847,653	1,847,653	1,847,653	1,847,653
R-squared	0.01152	0.01155	0.47001	0.47005
Mean of dependent variable	7.920	7.920	7.920	7.920

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis on consumers living in bordering counties. The sample includes consumers with a credit bureau record, an open credit card, and identifies consumers living in bordering counties within states that implemented utility shutoff moratoria or extended benefits programs (separately) and their neighboring counties within states that never implemented that policy using data from the 1991 Census Bureau Contiguous County File. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the *New York Times*, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

Table B.22: Policy Impact Estimates for 20-Week Extended Benefits UI Programs on Credit Card Delinquencies among Consumers in Contiguous Counties [PROVISIONAL RESULTS]

Percentage point change in the share of young adults (ages 20 to 29) with a delinquent credit card post-policy

Model	(1)	(2)	(3)	(4)
Description	**County FEs**	**County FEs with controls**	**Individual FEs**	**Individual FEs with controls**
Policy impacts				
Extended UI 20 wks	-0.06786	-0.06561	-0.14449	-0.14703
	(0.12256)	(0.12557)	(0.09428)	(0.09424)
Controls	No	Yes	No	Yes
Fixed effects	County and time		Individual and time	
Observations	1,549,634	1,549,634	1,549,634	1,549,634
R-squared	0.01039	0.01042	0.47036	0.47039
Mean of dependent variable	7.882	7.882	7.882	7.882

Source: Author's analysis of Urban Institute credit bureau data (as published in Martinchek 2024a).
Notes: This table shows the regression output of the difference-in-difference policy impact analysis on consumers living in bordering counties. The sample includes consumers with a credit bureau record, an open credit card, and identifies consumers living in bordering counties within states that implemented utility shutoff moratoria or extended benefits programs (separately) and their neighboring counties within states that never implemented that policy using data from the 1991 Census Bureau Contiguous County File. Differences in credit card delinquencies are measured in percentage points. Standard errors are listed in parentheses. *** denotes that the coefficient estimate is statistically significant at the $p < 0.01$ level, ** denotes that the coefficient estimate is statistically significant at the $p < 0.05$ level, and * denotes that the coefficient estimate is statistically significant at the $p < 0.10$ level. Column 1 presents estimates using county and time fixed effects, and column 2 estimates this specification with additional controls. Column 3 presents estimates using individual and time fixed effects, and column 4 estimates the same model using controls. Model 4 is the preferred specification. Control variables include indicators for other time-varying state-level policies (including garnishment suspensions, repossessions suspensions, and state-level eviction moratoria from the National Consumer Law Center; as well as differences in state-level timing of expanded eligibility through Pandemic Unemployment Assistance (PUA) and additional UI allotments (from Federal Pandemic Unemployment Compensation, or FPUC) from the COVID-19 US State Policy Database (CUSP)), data on states' COVID-19 cases and deaths from the New York Times, data on vaccination rates from the Centers on Disease Control and Prevention, data on state-level home price changes from the Urban Institute, data on state-level unemployment rates and on-time payment of UI benefits from the Bureau of Labor Statistics, and data on state-level business closures from the CUSP. In these data, a consumer is considered delinquent if they are more than 30 days past due on payments on at least one open credit card.

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