Inequality in High-Cost Borrowing and Unemployment Insurance Generosity in US States during the COVID-19 Pandemic

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Abstract

US consumers may turn to the private market for credit when income and government benefits fall short. The most vulnerable consumers have access only to the highest-cost loans. Prior research on trade-offs of credit with government welfare support cannot distinguish between distinct forms of unsecured credit due to data limitations. We provide insight on credit-welfare state trade-offs by leveraging a large sample of credit data that allow us to separate credit cards, personal loans, and alternative financial services loans, and to analyze heterogeneity in credit use by household income. We find that more generous state unemployment insurance benefits were associated with a lower probability of high-cost credit use during the first seven quarters of the COVID-19 pandemic. This inverse association was concentrated among consumers living in low-income households. Our results support theories that public benefits are inversely associated with the use of costly credit.

MAIN TEXT

Introduction

Given shortfalls of safety net programs in the United States, many Americans pursue private financial coping strategies such as borrowing on credit to make ends meet[1–4]. For some Americans, credit provides a crucial short-term source of liquidity, allowing them to take on debt that they then pay off in better times[5–7]. For others, borrowing results in expensive and ongoing unpaid debt, worsening economic insecurity [1,7,8]. Despite the documented importance of credit in household financial coping in the US, there is limited research in this area, especially compared to more commonly studied inequalities in income and poverty. In this paper, we construct a longitudinal dataset of unsecured credit use to explore the relationship between state unemployment insurance (UI) benefit generosity and disparities in high-cost unsecured debt. We ask whether UI generosity was associated with credit use for distinct types of unsecured credit and for distinct income groups across U.S. states in 2020 and 2021, a period during which UI benefits increased substantially and subsequently decreased corresponding to the expansion and then expiration of federal pandemic unemployment benefits.

Cross-national research describes a credit-welfare state trade-off: Americans have wide access to credit but less generous state support in times of crisis, whereas citizens in other rich countries receive more generous state support while often having lower access to credit[5,9,10]. In other words, credit operates as a substitute for welfare state benefits in settings with less generous welfare benefits but relatively open financial markets[10]. Studies of the US political economy describe a long history of federal reliance on credit and financial markets to resolve distributional pressures[4, 9-12]. The federal system also delegates significant power to US states in determining welfare state generosity[11,13]. A small but growing body of prior research tests the substitutive association within the United States by comparing across states with more versus less generous social welfare benefits. Some of this prior research finds evidence for the substitutive mechanism. Studies using the *Survey of Income and Program Participation* (SIPP) find that unemployed people take on significantly less total unsecured debt in states with more generous unemployment benefits and more generous Earned Income Tax Credits[9,11,14]. At the aggregate level, there is also evidence that states with less generous benefits exhibit a denser population of payday lenders[15]. However, other studies find that more generous welfare state benefits are associated with higher consumption and debt levels. One study estimates that state Medicaid generosity increases credit card debt as a result of lenders' supply response to borrowers' greater stability[16]. In the present context, this insight underscores the ambiguities in the direction of the relationship between UI benefit generosity and high-cost borrowing.

Thus while prior research provides some evidence to support the credit-welfare state tradeoff, the scientific basis for the theory remains incomplete. Theoretical ambiguities in credit-welfare state tradeoffs remain particularly in how higher- and lower-income populations respond to distinct types of social welfare[9,11]. For instance, it may be that while more economically secure households increase consumption and borrowing in response to generous social benefits[16], these social benefits may curb borrowing among more vulnerable and lower-income households who are more likely to borrow on credit to make ends meet[1,6,7]. Prior work has faced several limitations in testing income heterogeneity in trade-offs with high-cost borrowing. First, the types of credit accessible to the most vulnerable populations—especially alternative financial services and other subprime credit instruments—are much less commonly observed in existing data sources than prime credit instruments[1,4,6,7]. This may result in downwardly biased estimates of debt and, potentially, associations between social welfare policy generosity and debt, especially among low-income populations. Second and relatedly, nationally representative surveys with more extensive credit and debt modules have smaller samples of lower-income individuals and mainly ask about debts carried by higher income populations[4,9]. As a result, heterogeneity by income in responsiveness to policy variation is not well understood. Third, in the United States public benefits are often relatively modest, creating challenges for estimating associations between social policy generosity and indebtedness. Finally, prior work has been challenged by potential endogeneity of state social welfare policy generosity and debt holding among state residents, which may bias estimates of the association.

We build scientific insight into the credit-welfare state tradeoff with an empirical approach that helps address these limitations. We address the first two limitations by constructing a large dataset of detailed individual-level credit data that includes utilization of both traditional and alternative financial services (AFS) credit products among a one percent random sample of all U.S. individuals (and their household members). Our data allow us to examine variation in opening new unsecured credit accounts by type of debt, ranging from credit cards to higher cost personal loans, to the highest cost AFS loans. Credit cards are a widely held, traditional form of unsecured credit; however, people with lower incomes and poor credit histories may lack access to credit cards and, when they do gain access, may pay higher interest rates with lower credit limits[17]. Personal finance loans are a growing type of unsecured loan that have similar or higher interest rates than credit cards. AFS credit products represent particularly high-cost borrowing that is available to the highest risk borrowers. AFS loans are poorly tracked in survey and credit report data used in prior studies[18].

Capturing a wider range of credit instruments requires sufficiently large samples of economically vulnerable populations that use such credit. Our dataset includes a sufficiently large sample of vulnerable consumers and their household members that are most likely to use the highest-cost debt and, therefore, illuminates inequalities by household income levels in credit use. Our data also allow us to identify individuals who apply for and subsequently open a new credit card or originate a personal or AFS loan, which is critical for separating changes in consumption on existing credit lines from demand for new credit. (In supplemental analyses, we also examine inequalities in applications and in debt levels of these different types of credit.) Consumers in low-income households are of particular interest, as they were both more vulnerable to job loss during the pandemic and more likely to lack access to mainstream forms of credit relative to consumers in higher income households[19,20].

We address the third limitation of modest benefit amounts by studying the credit-welfare state trade-off during the COVID-19 pandemic, which provided unusually generous benefits but also unusually variable benefits across US states[21,22]. The pandemic and associated 'stay-at-home' orders led to unemployment at levels not seen in the United States since the Great

Depression. The U.S. unemployment rate increased from 3.5% in February 2020 to 14.7% in April 2020 and did not again fall below 5% until September 2021[23]. The U.S. government, like that of most wealthy countries, responded quickly by providing economic support to businesses, individuals, and households, including unprecedented levels of direct income transfers. Among the most important interventions was increased eligibility and benefit generosity in the Unemployment Insurance (UI) program. Under the Coronavirus Aid, Relief and Economic Security (CARES) Act of 2020 (P.L. 116-136), Unemployment Insurance (UI) benefit levels were federally subsidized by $600 per week from March 27, 2020, to July 31, 2020 and then by $300 per week until September 1, 2021. States were permitted to extend eligibility for UI benefits to include a wide range of workers who do not usually qualify, including self-employed, contract, freelance, and gig workers. The CARES Act also allowed states to extend benefits from a maximum of 26 weeks to 39 weeks.

Combined, these policies actually increased the financial security for many people and resulted in as many as 76% of unemployed workers being eligible to receive UI benefits that exceeded their lost wages at the peak of the program[21,22,24]. To the extent that a credit-welfare state tradeoff exists, generous UI benefits are expected to decrease reliance on high cost debt. Existing research finds an average decline in debt levels and debt use in the months immediately following the onset of the pandemic[25,26], but studies of the effects of government cash transfers during the pandemic, including UI, indicate that they substantially bolstered consumption among those who received them[27,28]. Thus, there is theoretical ambiguity even in the early months of the pandemic and is not yet clear whether expanded welfare generosity, like UI insurance, is linked with declining levels and disparities in high-cost debt.

Moreover, UI in the U.S. is decentralized, such that eligibility, access, and benefit levels vary considerably by state and the CARES act enabled even more state variability to emerge. This variation provides an opportunity to address the fourth limitation in prior empirical research–the potential endogeneity between state UI benefit generosity and individual credit use. Specifically, the CARES Act permitted—but did not require—the extensions to eligibility and benefits described above. In addition, about half of US states terminated Federal Pandemic Unemployment Compensation (FPUC) before it expired September 2021. Thus UI benefit generosity varied even more in 2021 as states opted out of federal UI benefit supplements at different points in time[21,22]. We leverage this source of exogenous policy variation to examine the relationship between changes in UI benefit generosity within a state and individual level credit use over time. We estimate two-way state and quarter-year fixed effects models, allowing us to better isolate the association of within-state variation in UI benefit generosity and heterogeneous use of unsecured credit.

We find that more generous state UI benefits were associated with a lower probability of unsecured credit use relative to less generous state UI benefits during the COVID-19 pandemic. The inverse associations between state UI generosity and unsecured credit use were concentrated among consumers in the lowest-income households for each credit outcome, including credit cards, new personal finance loans and AFS loans. Our results are consistent with expectations that generous government benefits can substitute for costly forms of financial coping during crisis periods—and that this relationship differs substantially by income. Our findings also underscore that the uneven and unequal generosity of the US social safety net left consumers in states with less generous UI benefits more vulnerable to high-cost subprime debt and deepened inequality during the COVID-19 pandemic.

Results

Bivariate correlations. Figure 1 shows scatterplots with lines of best fit between state UI generosity and the share of consumers living in a given state that had a newly opened credit card, personal loan or AFS account in their household from Q2 2020-Q4 2021. We find a small negative bivariate correlation between state UI generosity and the share of consumers with a new credit card. We find larger negative bivariate correlations between state UI generosity and the share of consumers with a new personal finance loan or AFS loan. Next we turn to the multivariate analyses to understand the association with state UI generosity across the three credit types for lower versus higher income groups.

[FIGURE 1 ABOUT HERE]

Regression results. We estimate multivariable associations between state UI generosity and each of the three unsecured credit use outcomes. Our estimates derive from linear probability regressions that control for a variety of individual-, ZIP Code-, and state-level characteristics that may confound the relationship between state UI generosity and our credit outcomes. We include quarter-year fixed effects to help account for period specific dynamics, including changes in the macro-economy as well as policy changes during our study period that affect all states. Our models also include state fixed effects to control for time-constant unobserved differences between states. We include interactions between state UI generosity and Q4 2019 household income to allow the associations of UI and credit to vary across more and less economically-advantaged populations of consumers. All standard errors are clustered at the consumer level. Complete details on our measures and modeling procedure are available in the *Methods* section. We present predicted probabilities derived from marginal effects for all results in the main text; tables reporting full model regression coefficients are available in the Supplementary Information.

Figure 2 displays the income-specific associations of state UI generosity on the probability of opening a new account for each of the three credit types, with mainstream credit cards on the left, personal finance loans in the middle, and AFS loans at the right. The x-axis represents the maximum unemployment insurance benefit in the state in which the consumer resides in a quarter, accounting for supplemental federal benefits where applicable. In each panel, the red line reports predicted probabilities for consumers in the lowest household income quartile, the blue line for consumers in the 25th-50th quartile, the gray line for 50th-75th quartile, and the black line for the highest income quartile. See Supplementary Table 2 for the full table reporting the linear probability regression coefficients, standard errors, p-values, and 95% confidence intervals for these models. We also report models for the averaged effects across income groups in Supplementary Table 3 but focus our discussion on heterogeneity by income given that we expect substantial variation in the relationship between UI benefit generosity and credit use by income.

Panel A of Figure 2 (left side) displays the income-specific associations for the probability of opening a new credit card. Consistent with the bivariate state-level correlations, estimates from our regression-adjusted individual-level models reveal an inverse relation between higher UI generosity and opening a new credit card, especially for consumers living in low-income households. The probability of taking out a new credit card was 2.2 percentage-points lower for the lowest-income consumers when state UI benefits were most generous relative to when state UI benefits were the least generous—a 9.7% difference in the probability of opening a new credit card account. For the second income quartile of consumers (25-50), we also find an inverse relationship, but with a smaller 3.7% difference in the probability of opening a new credit card account. For the two higher income quartiles, there is no statistically significant association between higher UI generosity and the probability of opening a new credit card. Our findings for credit cards thus support our expectation of income heterogeneity in state policy responsiveness.

Panel B of Figure 2 (middle) shows the income-specific associations for the probability of opening a new personal finance loan. We observe substantial heterogeneity by household income in the association between state UI generosity and the probability of taking out a new personal finance loan. Greater state UI generosity was associated with substantially fewer new personal finance loans among consumers from the lowest income households (beta = -0.003 [DF = 2,385,287], p-value = <0.001, 95% CI = -0.004, -0.002), while UI generosity had little, or a moderately positive, association with new personal finance loans for consumers from higher income households. For the lowest-income consumers, the probability of taking out a personal loan was 1.5 percentage-points lower for the lowest-income consumers when state UI benefits were most generous relative to when state UI benefits were least generous—a 38% difference in the probability of opening a new personal loan. In contrast, for each of the three higher-income quartiles the predicted probability of taking out a new personal finance loan is higher with greater UI generosity. Each higher quartile has a stronger positive association, perhaps due to a consumptive response among the higher-income consumers who engage the personal finance market.

Panel C of Figure 2 (right side) displays the income-specific associations for the probability of opening a new AFS loan, the costliest form of unsecured credit in our data. We find that the negative association between state UI generosity and the likelihood of new AFS loans was strongest for the lowest income consumers (beta = -0.003, [DF = 2,385,287], p-value = <0.001, 95% CI = -0.004, -0.003). In contrast, we find a moderate positive relationship between state UI generosity and the probability of having a new AFS loan for consumers from higher parts of the income distribution. For consumers from lower income households, an increase in state UI benefit generosity was associated with a decline in the probability of opening a new AFS loan: for the lowest-income consumers, the probability of taking out an AFS loan was 1.7 percentage-points lower when state UI benefits were most generous relative to when benefits were least generous—a 24% difference in the probability of opening a new AFS loan. Similar to the estimates for personal finance loans, for the three higher-income quartiles the predicted probability of taking out a new AFS loan is higher with greater UI generosity. Each higher quartile has a stronger positive association, perhaps due to a consumptive response among the higher-income consumers who engage the AFS market.

In sum, consumers from lower-income households consistently show an inverse association with UI benefit generosity across all three measures of credit use, including opening a new credit card, a new personal finance loan, and a new AFS loan, with more heterogeneity at higher income levels. In the case of personal finance and AFS loans, we even observe an increase in credit use for higher income consumers. These findings highlight the importance of accounting for income heterogeneity when studying the relationship between benefit generosity and credit use. Indeed, in our analysis sample, we find mixed results when we estimate models that do not account for income heterogeneity (e.g. excluding the interaction terms in our main models). For the average consumer, there is a small, statistically significant negative relationship between UI benefit generosity and opening new credit cards, but a small, statistically significant positive relationship between UI benefit generosity and personal loans and AFS loans (Supplementary Table 3). Our main results in Figure 2 demonstrate that these mixed findings for the average consumer reflect countervailing substitutive and consumptive mechanisms associated with UI benefit generosity that vary by income.

[FIGURE 2 ABOUT HERE]

Alternative specifications. In order to evaluate whether our results are sensitive to coding decisions, we test alternative measures of our key explanatory and outcome variables. To probe the robustness of our key explanatory variable, we re-estimate our models using *two alternative measures of state unemployment insurance generosity*. First, we test the UI replacement ratio, which captures the average ratio of UI benefits to pre-displacement wages in a state and quarter with predicted probability results presented in Supplementary Figure 1. Second, we use the minimum UI benefit to measure generosity, constructed in the same manner as when we use the maximum benefit to measure generosity with predicted probability results presented in Supplementary Figure 2. Our results remain largely consistent for both alternative measures, with the lowest income quartile consumers being less likely to open new accounts as state benefit generosity increases, and higher income consumers exhibiting insignificant or positive associations. For the UI replacement ratio, the magnitude of the negative association for the lowest income consumers is muted but still statistically significant and negative for all three credit types (credit card beta = -0.002 [DF = 2,385,287], p-value=0.000, 95% CI = -0.003, -0.001; personal loan beta = -0.0005 [DF = 2,385,287], p-value=0.000, 95% CI = -0.0007, -0.0004; AFS loan beta = -0.0003 [DF = 2,385,287], p-value=0.000, 95% CI = -0.0004, -0.0001). This more muted association may reflect the fact that the UI replacement ratio does not account for variation in the maximum benefit duration within a state over time. This demonstrates the value of our more comprehensive measure of UI benefit generosity that takes into account both the benefit amount and the benefit duration.

Third, to probe the extent to which our results might be driven by individual differences in consumers who are more likely to open new lines of credit (regardless of UI benefit generosity), we re-estimate our main models *controlling for lagged measures of the dependent* *variables* as of Q4 2019. Our results are nearly identical for credit cards and new personal finance loans, with slightly less heterogeneity observed by income for AFS loans. However, the lowest income consumers are still less likely to use AFS loans when UI benefits are less generous relative to when UI benefits are more generous (complete regression output for these models are available in Supplementary Table 4).

In a second set of alternative specifications, we re-estimate our models with different constructions of our outcome variables. Our main outcomes measure credit use defined as opening a new account. Our first set of alternative outcomes measure *whether consumers applied for each type of credit in a quarter regardless of subsequently opening an account* (predicted probability results presented in Supplementary Figure 3). Consumers may seek credit without opening a new account, for example if they are denied by a creditor, and there is some evidence that creditors restricted access to new accounts shortly after the onset of COVID-19[24]. Results for applying for new credit are largely consistent with our primary results for opening new credit. For the lowest income consumers, higher levels of UI benefit generosity are associated with a lower likelihood of applying for a new credit card, personal loan, and AFS loan, showing a stronger association for personal finance loan inquiries than for taking out a new personal finance loan. And, as in the main analyses, the association between UI generosity and each type of credit inquiry was insignificant or positive for higher-income counterparts. Thus inquiries, if anything, show a stronger inverse association with UI benefit generosity for low-income populations, which is informative of credit-seeking–though not necessarily receiving–in times of crisis.

Second, we examine the relation between state UI generosity and *currently outstanding debt balances* on credit cards, personal finance loans, and AFS loans (predicted probability results presented in Supplementary Figure 4). Despite the limitations of focusing on debt balances mentioned earlier, it is valuable to explore whether total debt follows the same pattern as new account opening. For personal finance and AFS loan balances, we find that results are quite consistent with those presented for new accounts and for credit seeking. The associations with current personal finance and AFS loan balances vary by income, such that the inverse associations were among consumers from the lowest-income households, consistent with our findings for new personal finance and AFS loan accounts, and positive associations for higher income groups. However, for credit cards, we observe no significant association between UI generosity and log credit card balance for the lowest income households (beta = -0.0007 [DF = 2,385,287], p-value=0.843, 95% CI = -0.0008, 0.0006). Consistent with results for new personal and AFS loan accounts, we observe moderate positive associations between UI generosity and log credit card balances for the higher income groups.

Third, we test an alternative outcome measure of *high credit card utilization*, defined as living in a household with one or more members who have used a high proportion of their available credit on credit cards (predicted probability results presented in Supplementary Figure 5). Opening a new credit card could occur without drawing on that credit, while new personal finance and AFS loan accounts entail actually taking on debt. Consistent with our main results, we find that the lowest income quartile consumers in states with more generous UI were less likely to have a high credit card utilization ratio. Moreover, this relation was insignificant or positive for higher income households.. Thus, the results for credit cards look most similar to the results for personal finance and AFS loans among consumers with a high degree of leverage on their credit card accounts.

Finally, we test whether our results are different when we take account of the Federal SNAP Emergency Allotment Benefit Supplements, for which there was some state variation in termination of the extension in 2021[29]. Our main analyses control for SNAP benefits, but leave out the $95 additional SNAP benefit that 8 states terminated early in 2021. The results remain quite similar when we take account of the Emergency Allotment, as reported in Supplementary Figure 6.

Discussion

Using a large sample of detailed credit report data and leveraging the variable timing of the expiration of Federal Pandemic Unemployment Insurance benefits, we find that more generous state UI benefits were associated with a lower probability of unsecured credit use for the lowest income households who are most vulnerable to economic shocks such as the COVID-19 crisis. For these individuals, we find an inverse association between state UI generosity and debt usage across heterogeneous debt types, including credit cards, personal loans and AFS loans. When state UI benefits were more generous, vulnerable consumers were less likely to turn to costly forms of unsecured credit to 'make ends meet.' In contrast, when state UI benefits were less generous, the lowest income consumers were more likely to seek and use high-cost forms of credit—likely exacerbating economic inequality and precarity. Our findings demonstrate heterogeneous associations for credit types and household income in a time of unprecedented benefit generosity.

While our study allows us to address several limitations of prior research, limitations remain in our research as well and we detail what we see as the most important here. First, we cannot observe whether a consumer is eligible for UI benefits in our data. Second, we only focus on substitutive associations with UI, while there are many other social supports that also may be associated with unsecured credit use. Third, even our additional of alternative financial services loans missed forms of debt-holding that are more common among low-income populations, including past due bills, child support arrears, and legal fines and fees. Fourth, our use of two-way fixed effects controls for many factors but still falls short of the causal identification possible in experimental designs. Finally, our study cannot speak to potentially significant racial inequalities in the relationship between UI and unsecured credit use.

Our work indicates several fruitful directions for future research, including to address the limitations of this study. First, additional research is needed on those with job loss or economic hardships who do not qualify for UI benefits, especially in the absence of pandemic-related expanded eligibility. Second, future work should examine whether the substitutive associations we find here hold for transfers other than UI, including expansions of the child tax credit and increased eligibility and benefit generosity in a range of means-tested programs[30]. These programs may be more influential for the most vulnerable populations and may have implications for stronger substitutive associations with the highest cost forms of credit. Our analysis may therefore be considered a more conservative test of credit-welfare state trade-offs for the credit used by the most vulnerable populations. Future research on other social welfare programs that specifically target the most vulnerable populations is warranted.

Third, future work can consider other forms of debt that do not appear in traditional or alternative credit data, such as bank overdraft amounts or unpaid utility bills[8,31,32]. There may also be important interconnections to state-imposed or enforced debt including child support arrears and legal debt[33,34]. We were primarily interested in credit-seeking, and thus focused on prospective forms of credit in this study, like credit cards and loans rather than retrospective debt obligations not obtained through credit markets[4]. However, retrospective debt obligations may be more common among the most vulnerable consumers, including those who do not hold a credit record or who do not access credit markets[4]. Fourth, while our two-way fixed effects approach is more effective than traditional OLS models for handling unobserved heterogeneity, we are unable to estimate causal effects in this study including due to limitations associated with staggered timing in policy adoption[35–39]. Policy experiments may provide an opportunity for an alternative causal specification to further investigate the relationships we study here.

Finally, future work is needed on racial inequality in addition to income disparities. UI and other state benefits may be distributed in racially unequal patterns and racial discrimination and inequalities in access may result in high exposure to high-cost credit among Black and Hispanic populations[40–42]. In particular, economic conditions improved fastest for the highest-income groups, resulting in what some have characterized as a k-shaped recovery such that the lowest-income groups, which disproportionately include marginalized racial and ethnic populations, continued to face unemployment and underemployment far longer than more privileged workers in positions more easily transitioned to remote work[43,44]. Despite the strengths of our data, information on race and ethnic identity is not available in credit report data and thus we are unable to explore differences by race.

We close with three main conclusions. First, our research provides evidence that helps resolve ambiguities in theories of credit-welfare state tradeoffs and substitutive relationships between social benefit generosity. We find considerable heterogeneity in the association of UI benefit generosity and debt across household income for all three distinct types of unsecured debt. The substitutive association concentrates among the lowest-income populations, whereas higher income groups showed no association (for credit cards) or a positive association consistent with more of a consumptive mechanism. Second, we were able to observe these findings in part because we had detailed data on heterogeneous debt types, including those most likely used by low-income groups. These findings underscore the need for research to examine debt holding for distinct credit types and to move beyond models of combined debt levels for all income groups together. Finally, and most generally, our findings add to research indicating that the unprecedented Unemployment Insurance generosity stabilized household finances during the pandemic. Whereas most prior work has focused on poverty and material hardship, our results indicate that there was also protection against unsecured debt taking for the lowest income consumers, including the highest-cost AFS loans that are most used by low-income populations[21–22]. Our work further bolsters policy proposals that consider expanding UI to broader recipients[22]. Understanding inequality in credit and debt captures crucial but often overlooked dimensions of disadvantage and economic insecurity for vulnerable Americans on the edge.

METHODS

This research was approved by The Ohio State University's Behavioral and Social Sciences Institutional Review Board. This study received a waiver of the consent process given its use of deidentified credit data on individuals collected for non-research purposes. No individuals were contacted or compensated for this research, and this study was not preregistered.

Data

We draw our study sample from proprietary data of the consumer credit bureau Experian. Experian collects data representing almost 300 million unique consumers spanning more than 90 percent of the US population age 18 and older[45,46]. Experian data include information on credit accounts reported by mainstream creditors such as banks, mortgage companies, credit card companies, and auto lenders, as well as collections for both credit and non-credit accounts including medical and utility bills that were sent to a collection agency. We also draw data from Clarity Services (hereafter, Clarity), a subsidiary of Experian that aggregates alternative financial services (AFS) data reported by creditors offering small dollar, high cost, and shorter-term credit including payday loans, single-period micro loans, and high interest rate short-term installment loans. Clarity data capture over 70% of non-prime consumers[47-49]. We merge data from Clarity to the Experian data using the unique consumer identification number. By merging traditional credit information from Experian with AFS credit information from Clarity, we observe heterogeneous forms of unsecured credit use.

For this study, we acquired a 1% random sample of US consumers and their household members in Experian credit data for each quarter from Q42019 through Q42021. We identify the random sample using a sampling strategy that flags all consumers in Experian's database who have the same last two-digits of their consumer pin. The consumer pin is a nine-digit number similar to a Social Security number and is randomly generated and time invariant for each consumer. Similar to the New York Fed Consumer Credit Panel (CCP)[50], this sampling strategy allows us to trace the same individuals across time and to replenish the panel with consumers who enter Experian's database who have the same last two-digits we sample. This provides a consistent nationally representative sample of consumers in Experian's database every quarter. We also have credit data for all adult household members of the randomly selected consumer, defined as consumers living at the same address as the randomly selected consumer in a quarter. We use these data to construct measures of credit use within the household of the randomly selected consumer in a particular period, as randomly selected consumers may have access to the credit of other people living in their households. Our random sample is thus at the consumer level, but we use data from household members to construct particular analysis variables.

Sensitivity analyses with all analysis variables at the consumer level without taking into account household members show similar results (available by request from the authors).

We supplement the credit data from Experian with various state and ZIP Code level datasets (described in the measures section below). We assign each individual in the credit data to a particular state in a given quarter based on the ZIP Code of their address. Most 5-digit ZIP Codes do not cross state lines but, for those that do, we use the crosswalk from the Missouri Census Data Center to assign the ZIP Code a "primary state" based on where the largest population in the ZIP Code falls. In order to protect consumer record privacy, we received only 3-digit ZIP Codes for some consumers who live in low-population areas of the country. In those cases, we similarly assign a state based on the state with the largest percentage of population.

Analytic Sample. To ensure a balanced panel, we restrict our sample to randomly selected consumers in the credit data in all quarters of our study. We make a number of additional exclusions to ensure that our sample represents consumers with active credit files, following similar practices as those developed for the NY Federal Reserve Consumer Credit Panel[50]. We exclude individuals who are flagged by Experian as deceased in a quarter, either through creditor reports or social security administration data, as some creditors may continue to report on an individual after they are deceased. We also exclude observations with missing data for social security number or who have only inquiries but no accounts in their credit file, as these observations are more likely to be fragmented credit files (e.g., an incomplete, duplicate credit record for an individual who is already in the credit data) rather than active credit files for unique individuals. This exclusion also omits people in the U.S. population without social security numbers (such as undocumented workers), but who may have credit. We are unable to identify the reason for missing social security numbers in our data; however, most people without a social security number are ineligible for UI benefits and thus are not the focus of this study. In addition, we exclude consumers who are always missing data on age, as these may also reflect duplicate or false files. Sensitivity analyses including these consumers show similar results.

Our final analytic sample consists of a balanced panel of 2,385,373 unique consumers who are present in the data for each of the following quarters: Q4 2019, Q2 2020, Q3 2020, Q4 2020, Q1 2021, Q2 2021, Q3 2021, and Q4 2021. We measure baseline characteristics in Q4 2019 before the COVID-19 pandemic began and measure indicators of unsecured credit use from Q2 2020 through Q4 2021 following the onset of the pandemic (see below for further details on our measures). We exclude Q1 2020 from our analyses given that it was characterized by the initial shock of the pandemic and preceded major policy responses. Our effective analysis sample is 16,697,611 consumer-quarter observations from Q2 2020 through Q4 2021. No statistical methods were used to pre-determine the size of our random sample, but our sample sizes are similar to or larger than those reported in previous publications[6,11,27]. Our sample is sufficiently large to be representative in all 50 states, ranging from 295,793 unique consumers in California to 3,540 in Wyoming. (Supplementary Table 1 presents the full sample distribution by state.)

It is important to note that our analysis sample is limited to people with Experian credit records and thus results are only generalizable to people with credit records. However, most people have credit records, even if they do not use credit or have active credit accounts. For example, some people only have collections accounts and thus are not actively using credit per se; however, they appear in Experian credit data because of the collection account. We found that most AFS users have traditional credit records, with 95 percent of the consumers in the Clarity AFS data also appearing in Experian's credit data. Young adults under the age of 22 are the largest demographic group who are missing from credit data due to not having any credit accounts or collections[51].

Measures

Heterogeneous unsecured credit use. Our main analyses focus on three outcomes capturing the use of different types of unsecured credit. In each quarter, we specify dummy variables indicating whether a consumer or anyone in their household opened any new credit card, opened any new personal finance loan, and opened any new AFS loan. These three types of unsecured credit capture different population segments of the market, with credit cards being the most common. We analyze opening new accounts in our main analyses as a particularly informative measure of credit seeking that occurred after the onset of the pandemic rather than focusing on debt balances, which may include spending before the pandemic. Variation in debt balances also reflects differences in debt repayment by borrowers as well as actions by lenders to charge off delinquent debts.

Our first measure of unsecured credit use is a dichotomous indicator for whether anyone in the consumer's household opened a new credit card in a given quarter. Credit cards include revolving bankcards, charge cards, oil cards, and retail or department store cards. The new credit card variable includes new accounts for which someone in the household is the owner of the credit card, as well as new accounts for which someone in the household is not the owner of the credit card but is an authorized user. We exclude housing-related revolving debt (e.g., home equity lines of credit) because our focus is on unsecured borrowing. Consumers in households with new credit cards tend to be more socioeconomically advantaged than consumers opening other types of unsecured credit (see Table 1 in the main text).

Our second measure of unsecured credit use is a dichotomous indicator for whether anyone in the household opened a new personal finance loan in a given quarter. Personal finance loans are installment loans. We include only personal finance loans from a company designated as a personal finance lender and exclude those from traditional depository institutions. Our measure therefore captures higher-cost personal loans, including those from the growing portion of the personal loan market constituted by digital lenders or "fintechs," a trend that intensified during the first years of the COVID-19 pandemic[52]. Most personal finance loans are relatively small; the average balance for loans during 2020-2021 was $6,000. In our data, consumers who live in households with new personal finance loans occupy a middle socioeconomic position relative to consumers opening other types of unsecured credit (see Table 1 in the main text).

Our third measure of unsecured credit use is a dichotomous indicator that captures whether the consumer or anyone in their household took out a new AFS loan in a given quarter. We include all types of AFS loans, including single payment and (short-term) installment loans, from any lender who reports to Clarity Services. The AFS market is distinct from the institutions that report to Experian and thus loans reported in the Clarity database provide unique insight on high cost credit use.. Relative to credit cards, the share of consumers opening a new AFS loan in a given quarter is small; however, consumers who turn to AFS represent a particularly vulnerable and often overlooked market segment.

In supplemental analyses, we measure debt balances for unsecured credit cards, personal loans, and AFS accounts (separately) as of a given quarter. We measure debt balances by type of credit at the household level and transform the values using a natural log to correct for the skewed distribution. We add a small positive constant ($1) before taking the log to keep those with $0 in debt in the sample.

Unemployment insurance generosity. We construct a time-varying measure of state UI generosity in two steps. First, we calculate the maximum possible claimant benefits for a state in a given quarter, which is a function of both length of benefit availability and weekly benefit amount, as in prior studies[24]. Specifically, as of each quarter, we multiply the maximum number of weeks a person can receive UI benefits by the maximum weekly benefit amount they can receive. All data for the generosity measures were drawn from the U.S. Department of Labor's report on "Significant Provisions of State UI Laws"[53]. We adjust all UI benefit amounts to constant Q4 2021 dollars using the Consumer Price Index-All Urban Consumers series.

Next, we adjust the state maximum UI benefit amount to include the additional Federal benefits associated with the Federal Pandemic Unemployment Compensation (FPUC) program. Following prior studies[54], we add $600 per week to the maximum benefit for all states from Q2 2020 to Q3 2020. We then add $300 per week to the maximum benefit for all states from Q4 2020 to Q1 2021. Beginning in Q2 of 2021, states were allowed to terminate their participation in the FPUC program[53]. We allow for different timing of state termination by adding $300 per week to the state maximum benefit only for states that did not terminate FPUC in Q2 2021. We stop adding FPUC benefits to the state maximum benefit for all states in Q3 2021, as the FPUC program expired in September of 2021. Thus, our UI generosity measure relies exclusively on state policy design, and not on individual claim eligibility or claiming behavior that may be influenced by conditions that also affect credit choices. Some prior research addresses potential endogeneity by using detailed individual-level earnings histories to construct individual-level simulations of potential UI benefits[55,56]. While our credit data are extensive, they do not include individual level earnings histories. Our approach addresses endogeneity by measuring UI benefit generosity as a function of changes in state policy over time rather than changes in individual behaviors. Figure 3 maps variation in average maximum UI benefit generosity across the 50 U.S. states from Q2 2020-Q4 2021. Average maximum UI benefit generosity varied widely from $44,091 in Massachusetts to $7,879 in Florida.

[FIGURE 3 ABOUT HERE]

Figure 4 shows that there was substantial temporal variability in FPUC-adjusted state UI maximum benefit amounts. Including FPUC benefits in our measure of state UI generosity allows us to leverage heterogenous timing in the expiration of Federal UI benefits in our estimation of associations with credit outcomes.

[FIGURE 4 ABOUT HERE]

Socio-demographic characteristics. We measure socio-demographic characteristics at the individual and ZIP Code levels as of the fourth quarter of 2019. At the individual level, Experian data includes a measure of imputed household income. Because this value is imputed using credit data, each individual consumer receives an income value. We take the average of the imputed income value across all members in a consumer's household. Validation of prior credit bureau income imputations against matched CoreLogic and Home Mortgage Disclosure Act income data demonstrates a close match, with a median gap of $2,000[57]. Additionally, we control for the consumer's credit score (VantageScore 4.0), measured as the average credit score for adults residing in the household of the randomly selected consumer as of Q4 2019. Following industry thresholds, we create a 5-category credit score measure: deep subprime (579 or less), subprime (580-619), near prime (620-659), prime (660-719), and super-prime (720 or greater). Lastly, at the individual level, we include a dichotomous variable for whether any adult in the household of the randomly selected consumer had a credit card balance as of Q4 2019 (excluding amounts that are severely past due or charged off by the creditor). This measures the extent to which the consumer had an active credit card account prior to the onset of the pandemic.

At the ZIP Code level, we include the racial and ethnic composition of the ZIP Code of residence as of Q4 2019, as individual data on race and ethnicity are not included in the Experian data. Using 2019 5-year estimates from the American Community Survey (ACS), we construct majority neighborhood racial/ethnic composition, with categories being White, Non-Hispanic Black, Hispanic, or no majority[58]. We also control for the ZIP Code unemployment rate and median household income sourced from the 2019 5-year estimates of the ACS[58]. ZIP Code characteristics are measured at the 3-digit level for consumers who never have a 5-digit ZIP Code during our sample period.

Table 1 reports the demographic profile of consumers who opened each form of credit. New AFS users are, on average, the most disadvantaged across many dimensions. Compared to the general population, consumers with a new AFS loan were more likely to live in households in the lowest income quartile, had lower credit scores, and were more likely to live in majority Black and lower income ZIP Codes. Consumers opening a new credit card, in contrast, were more dispersed across the household income and credit score distributions and tended to live in whiter and more affluent ZIP Codes. Consumers with a new personal finance loan fell in between on these characteristics.

[TABLE 1 ABOUT HERE]

State-level control variables. We control for a number of time-varying factors at the state level that may associate with both UI benefit generosity and credit use. Controls measured at annual intervals include state gross product per capita from the Kentucky Center for Poverty Research National Welfare Database as of 2019[59], the percent change in state gross product relative to the prior year, whether the governor was a Democrat, presence of a state Earned Income Tax Credit (EITC), presence of a refundable state EITC, share participating in the Supplemental Nutrition Assistance Program (SNAP), and the maximum SNAP benefit amount for a family of four. Controls measured at quarterly intervals include the state unemployment rate from the Bureau of Labor Statistics, as well as indicators for the presence of Covid mitigation policies in effect in a given state and quarter. We draw data on state-wide stay at home orders, and nonessential business shutdowns from the COVID-19 U.S. State Policy

Database[60], and we draw the presence of a state utility shutoff and eviction moratoria from the Eviction Moratoria Housing Policy Dataset[61]. Importantly, because of state regulations that place restrictions on AFS lenders, we include a time-varying four-category ordinal index of small-loan restrictiveness based on data from the National Consumer Law Center and the Center for Responsible Lending[62,63]. The index is calculated as the count of state restrictions on payday loans, 6-month $500 installment loans, and 2-year $2,000 installment loans, where restrictions are defined as the presence of an interest rate of 36% or less. We code state-year observations in which payday lenders do not operate in a state as being restrictive on payday loans.

Models

The general empirical model for our analysis takes the following form:

$$Y_{ist} = \beta_0 + \beta_1(\textit{Unemployment generosity}_{st}) + \beta_2(\textit{Household income quartile}_i) + \beta_3(\textit{Unemployment generosity}_{st})*(\textit{Household income quartile}_i) + \boldsymbol{I'}_i + \boldsymbol{Z'}_z + \boldsymbol{S'}_{st} + \gamma_t + \lambda_s + \varepsilon_{it}$$

where the outcome (Y_{ist}) is a particular credit outcome for person i in state s as of quarter t. Our primary explanatory variable is a measure of state unemployment generosity in a quarter ($\textit{Unemployment generosity}_{st}$), and in particular, its interaction with the quartile of household income for an individual ($\textit{Household income quartile}_i$). We control for socio-demographic characteristics with a vector of time-invariant individual characteristics ($\boldsymbol{I'}_i$) and a vector of time-invariant ZIP Code characteristics ($\boldsymbol{Z'}_z$), both measured as of the fourth quarter of 2019. We also control for a vector of time-varying state characteristics ($\boldsymbol{S'}_{st}$). We include quarter-year fixed effects (γ_t) that capture unobserved changes in the macro-economy over time, including the effects of the pause on federal student loan payments, stimulus checks, child tax credits, and other federal Covid policies that applied to all states contemporaneously. We include state fixed effects (λ_s) to capture unobserved time-invariant characteristics of states. The random error term (ε_{it}) is clustered within the consumer level (i). We use linear probability models to estimate these equations.

By including both state and time (quarter) fixed effects, our model is similar to a two-way fixed effects model with a staggered treated, where the treatment here is the continuous value of UI benefit generosity in a state and quarter. The literature in econometrics and related fields has highlighted the potential problems of studies that estimate the effects of policies using the staggered timing of when states adopt the policy[35-39]. ~~In our study, the “treatment” is $1 more or less UI generosity from a state in a given quarter. UI generosity varies pre-COVID, changes (increases) during COVID periods relative to pre-COVID periods, and then goes back down as federal and state UI extensions gradually expire. We use this state UI generosity variation to estimate the effect of a continuously varying policy parameter on residents’ financial circumstances.~~ In essence, the policy’s effect could be heterogeneous across units (here states), and yet treatment effect estimates must arise from the comparison of different states in untreated and treated conditions at a given time. ~~We recognize that t~~This could create potential bias in our estimates and thus our estimates should not be interpreted as causal treatment effects of UI benefit generosity.

Data availability statement: The credit panel data that support the findings of this study are proprietary data of the Experian Corporation and used under license for the current study and thus are not publicly available. We draw unemployment insurance measures from publicly available data from the U.S. Department of Labor Office of Unemployment Insurance, Significant provisions of state unemployment insurance laws effective January 2022. State and ZIP Code control variables derive from the publicly available 2019 5-year estimates from the American Community Survey, the publicly available University of Kentucky Center for Poverty Research National Welfare Database, and measures created from the publicly available National Consumer Law Center Small dollar loan products scorecard and Center for Responsible Lending reports. State and ZIP dataset including unemployment insurance measures are available by request from authors.

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Competing interests: The authors declare no competing interests.

Tables

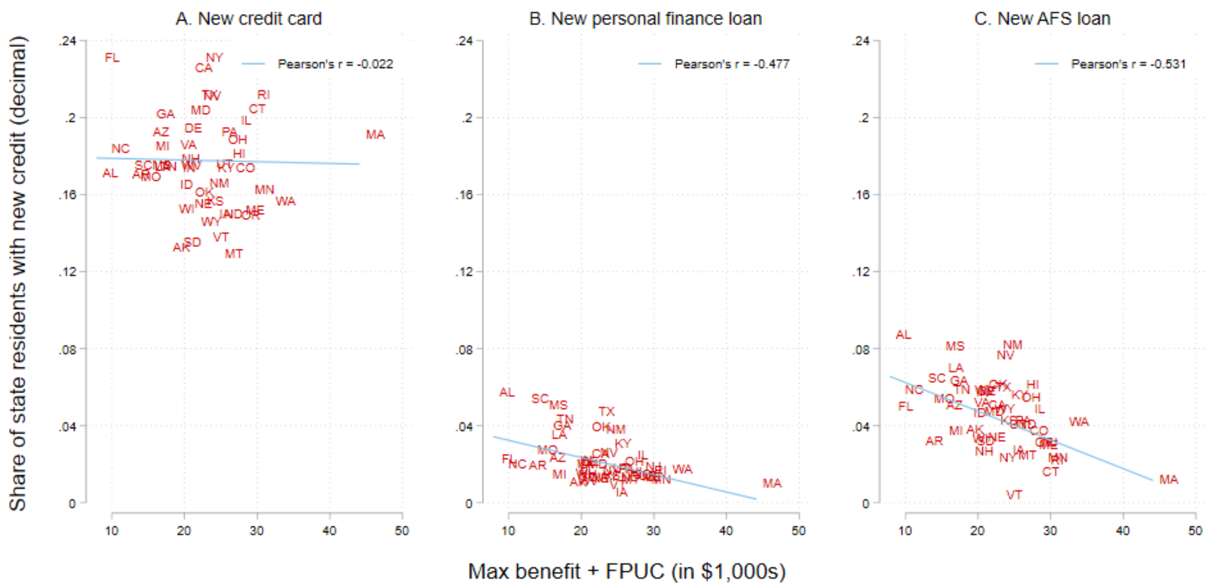
Table 1. Summary statistics by new credit card, personal finance loan, and AFS loan, Q2 2020-Q4 2021

	Full sample Mean	(SD)	Has new credit card Mean	Has new personal finance loan Mean	Has new AFS loan Mean
Consumer credit use outcomes					
New credit card account in last 3 months	0.20		1.00	0.39	0.34
New personal finance account in last 3 months	0.03		0.05	1.00	0.17
New AFS account in last 3 months	0.05		0.08	0.32	1.00
State unemployment insurance generosity					
State maximum UI benefit (in $1,000s)	20.34	9.28	19.58	19.08	19.16
Individual-level control variables					
Household income p0-p25, Q4 2019	0.26		0.29	0.50	0.57
Household income p25-p50, Q4 2019	0.23		0.27	0.25	0.27
Household income p50-p75, Q4 2019	0.25		0.25	0.15	0.12
Household income p75-p100, Q4 2019	0.26		0.20	0.10	0.04
Credit score: deep subprime (<580)	0.15		0.15	0.32	0.41
Credit score: subprime (580-619)	0.09		0.12	0.20	0.22
Credit score: near prime (620-660)	0.11		0.15	0.18	0.18
Credit score: prime (660-719)	0.20		0.23	0.18	0.14
Credit score: super prime (>=720)	0.45		0.35	0.12	0.05
Had credit card balance, Q4 2019 (0,1)	0.85		0.92	0.85	0.83
ZIP Code-level control variables					
Majority White ZIP Code, 2019	0.69		0.63	0.58	0.57
Majority Black ZIP Code, 2019	0.05		0.06	0.08	0.10
Majority Hispanic ZIP Code, 2019	0.09		0.12	0.16	0.14
No majority ZIP Code, 2019	0.17		0.19	0.18	0.19
Unemployment rate, 2019	5.30	2.54	5.44	5.85	6.06
Median household income (in $1,000s)	70.37	28.18	70.11	63.30	61.69
State-level control variables					
Unemployment rate	7.13	3.25	6.93	6.90	7.07
State product per capita (in $1,000s)	66.06	12.55	67.02	64.13	64.02
Percent change in state product per capita	4.75	6.53	5.26	4.67	4.76
Governor is Democrat (0,1)	0.55		0.55	0.45	0.50
Presence of state EITC (0,1)	0.60		0.60	0.50	0.53
Presence of refundable state EITC (0,1)	0.50		0.51	0.39	0.42
Percent of residents in SNAP program	0.12	0.03	0.12	0.13	0.13
Max SNAP benefit for family of four (in $1s)	668.13	40.92	669.28	666.66	668.58
State stay at home order (0,1)	0.17		0.15	0.15	0.18
State closures of non-essential businesses (0,1)	0.14		0.11	0.12	0.15
State utility shutoff moratoria (0,1)	0.40		0.41	0.34	0.35
State eviction moratoria (0,1)	0.51		0.52	0.43	0.46
Small-dollar loan restrictions (range: 0-3)	1.58	1.04	1.63	1.37	1.42
Observations	16,697,611		3,286,141	426,850	801,217

Note: New credit outcomes indicate whether a consumer or anyone in their household opened any new credit card, opened any new personal finance loan, and opened any new AFS loan. "AFS" is alternative financial services.
Source: 1% national random sample of consumers with credit reports and their household members. Experian data merged with Clarity data from AFS lenders.

Figures

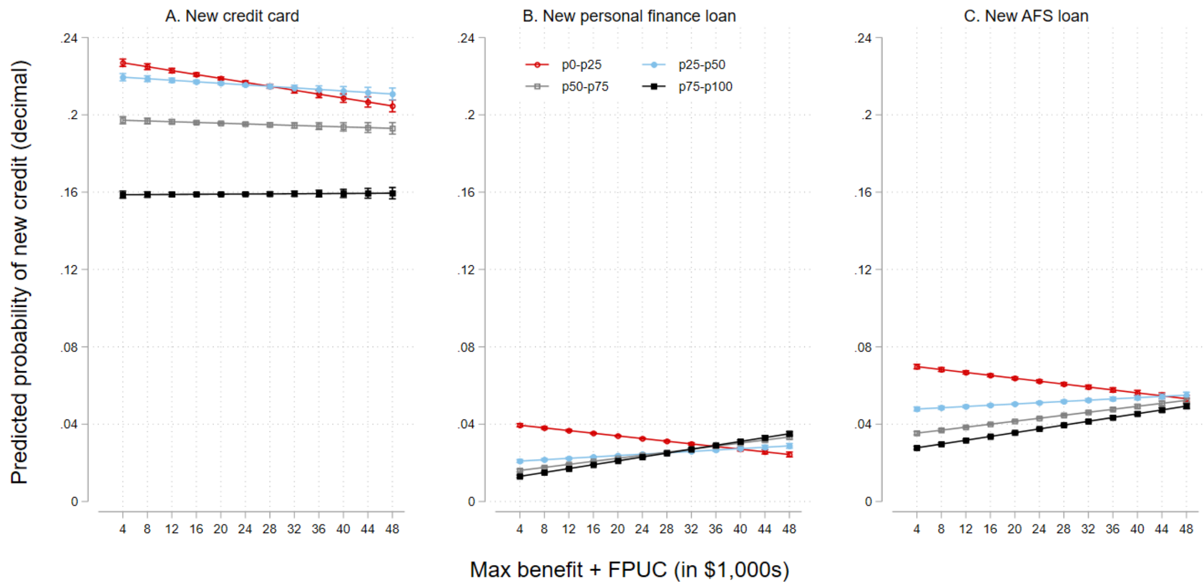
Figure 1. State-level bivariate correlations between state UI generosity and new credit card, personal finance loans, and AFS loans, Q2 2020-Q4 2021 (N = 50 US states).



Notes: This figure displays state-level scatterplots with linear lines of best fit and accompanying correlation coefficients for the new credit outcomes and the FPUC-adjusted maximum UI benefit, averaged over Q2 2020-Q4 2021. Panel A shows the results for new credit cards; Panel B shows the results for new personal finance loans; and Panel C shows the results for new AFS loans. P-value for Pearson's correlation coefficient (r) between UI maximum benefit and new credit cards is 0.907. P-value for Pearson's correlation coefficient (r) between UI maximum benefit and new personal finance loans is <0.001. P-value for Pearson's correlation coefficient (r) between UI maximum benefit and new personal finance loans is <0.001. "AFS" is alternative financial services. "AFS" is alternative financial services.

Source: Authors' analysis of 1% national random sample of consumers with credit reports and their household members from Experian, merged with Clarity data from AFS lenders and State UI data from "Significant Provisions of State UI Laws," U.S. Department of Labor.

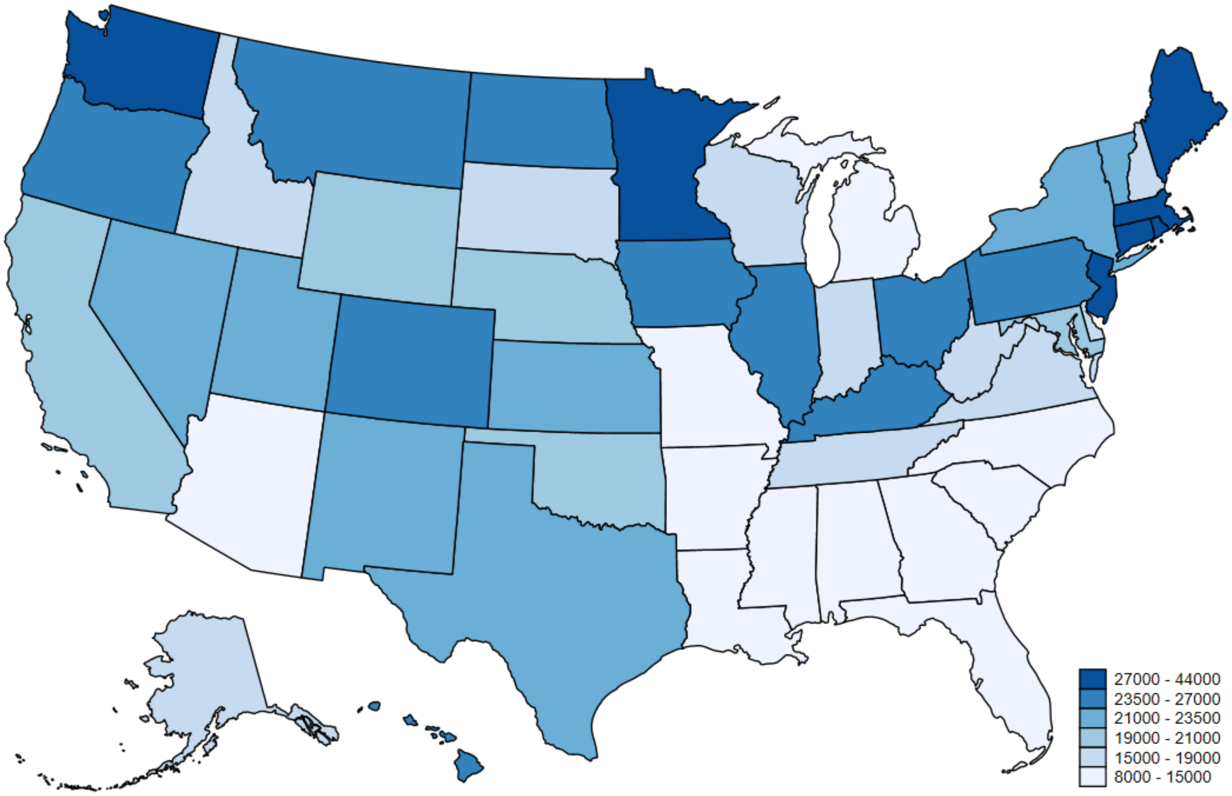
Figure 2. Associations of state UI generosity and new unsecured credit card, personal finance loan, and AFS loan by Q4 2019 household income, Q2 2020-Q4 2021 (N = 16,697,611 consumer-quarter observations).



Note: This figure plots predicted probabilities from linear probability regressions predicting new credit during Q2 2020-Q4 2021, adjusted for state and quarter fixed effects and individual, state, and ZIP Code level covariates. Panel A shows the results for new credit cards; Panel B shows the results for new personal finance loans; and Panel C shows the results for new AFS loans. Data are presented as predicted probabilities +/- 95% confidence intervals. “AFS” is alternative financial services. Legend category definitions: “p0-p25” includes consumers in the bottom household income quartile; “p25-p50” includes those in the lower-middle household income quartile; “p50-p75” includes those in the upper-middle household income quartile; “p75-p100” includes those in the top household income quartile. State max UI benefit on the x-axis ranges from the minimum to the maximum value.

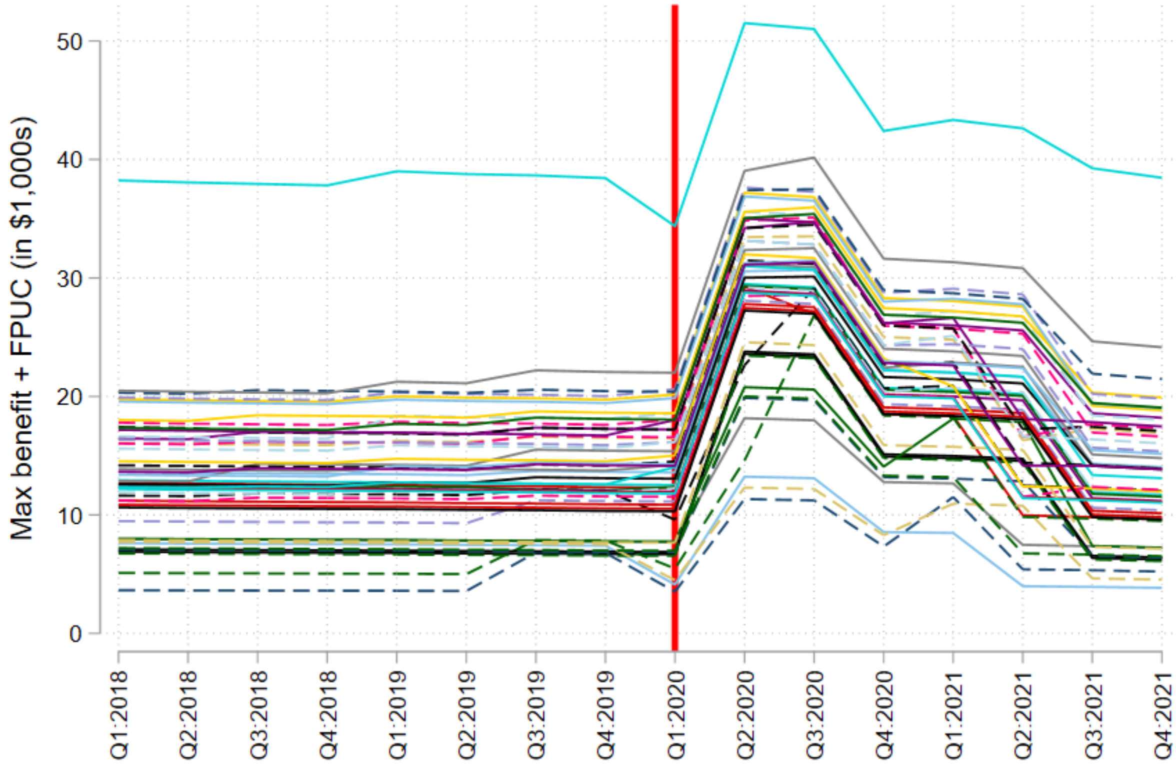
Source: Authors’ analysis of 1% national random sample of consumers with credit reports and their household members from Experian, merged with Clarity data from AFS lenders and State UI data from “Significant Provisions of State UI Laws,” U.S. Department of Labor.

Figure 3. State variation in maximum unemployment insurance benefits, average across states during Q2 2020-Q4 2021 (N = 50 US states).



Note: Figure 3 maps the average maximum dollar amount of unemployment insurance benefits across 50 U.S. states during Q2 2020-Q4 2021. The maximum unemployment insurance benefit is calculated as the product of the maximum number of weeks a person can receive unemployment benefits and the maximum weekly benefit amount, adjusted for additional FPUC benefits if applicable. Darker shades indicate higher maximum UI benefits.
Source: Authors' compilation and visualization of data reported in "Significant Provisions of State UI Laws," U.S. Department of Labor.

Figure 4. Temporal variation in maximum unemployment insurance benefits, Q1 2018-Q4 2021 (N = 50 US states).



Note: Figure 4 shows state-level trends in the FPUC-adjusted maximum unemployment insurance benefit from Quarter 1 2018 to Quarter 4 2021 across 50 U.S. states. Each trend line reports results for one U.S. state, with lines differentiated by color and by solid versus dotted patterns. The maximum unemployment insurance benefit is calculated as the product of the maximum number of weeks a person can receive unemployment benefits and the maximum weekly benefit amount, adjusted for additional FPUC benefits if applicable. The vertical line marks the onset of the Covid-19 pandemic in the U.S. in Q1 2020. Each trend lin relatecs
Source: "Significant Provisions of State UI Laws," U.S. Department of Labor.

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