Nepo Credit: The Effect of Borrowed Credit Histories

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Abstract

The intergenerational transfer of credit histories through authorized user (AU) status affects credit outcomes. About 16% of young adults benefit from AU status each year, gaining credit histories that pre-date their own financial activity. Using variation in the age at which individuals are added as AUs, we identify substantial gains to AU status: credit scores rise by 22-42 points, and access to credit cards and credit in broader markets increases. However, AU borrowers are more likely to default than others with similar credit scores, suggesting that AU histories inflate scores and reinforce inequality in credit access.

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1. Introduction

Access to credit allows households to smooth their consumption and invest in productive physical and human capital, which can facilitate upward mobility (Gross and Souleles, 2002; Becker and Tomes, 1979, 1986). Credit can be particularly useful for young adults, whose current income is often low relative to their expected future income. However, young adults typically have short borrowing histories, or none at all, which can make them opaque to lenders. Consumer credit scores provide lenders with information about borrower quality, so that lenders can allocate and price consumer credit effectively (Chatterjee et al., 2023).

But what if a borrower's seemingly observable credit quality is not their own? In the US credit system, it is common for more than one person to have access to, but not joint responsibility for, a shared credit account such as a credit card, through authorized user (AU) status. Importantly, authorized users benefit from the account's repayment history on their credit report. Therefore, in addition to using the credit line, AUs are, in effect, borrowing a piece of the sponsor's credit history. The practice of making children AUs on parents' credit cards has become increasingly common, with up to 16% of 21-year-olds being AUs in recent years (see Figure 1).

[Insert Figure 1 Here]

In this paper, we use credit bureau data for a representative sample of young adults aged 18-25 to study the impact of including AU accounts in the US credit scoring system. Our analysis proceeds in four steps. First, we examine the effect of AU account additions on young adults' credit scores. Second, we estimate the effect of AU status on young adults' access to credit across several credit products. Third, we study whether credit score increases resulting from AU account additions appear warranted based on ex post delinquencies and borrower financial performance. Finally, we document the correlation between AU account prevalence and ZIP code income and discuss the implications for inequality in credit markets and other settings that use credit scores.

To study the impact of AU accounts on credit outcomes, we use two difference-in-differences approaches. Our first approach focuses on the extensive margin, comparing young adults who gain AU status after entering the credit bureau data (the treated group) to young adults who never gain AU status by age 25 (the control group). The design includes individual fixed effects to account for persistent differences in characteristics that may correlate with whether the borrower gains AU status. We also control for time-varying borrower and ZIP code characteristics as well as state-year fixed effects. In addition to this main specification, we also conduct a matched version of this test that selects control units that match the treated units on the following dimensions: year, age, non-AU debt, credit score, and ZIP code income.

Our second approach is designed to eliminate any remaining selection bias inherent in gaining AU status. Specifically, we implement a second difference-in-differences design that restricts the sample to only individuals who gain AU status and exploits an intensive margin: the *length* of the credit history added through the AU account (i.e., the account age of the sponsor's credit card). This design compares two young adults who gain AU status in the same year and at the same age, with similar non-AU debt, credit scores, ZIP code income, and AU account credit limits, but who differ in whether the added account has a longer or shorter history. In particular, we define the treated group as young adults for whom the AU account is older than any of their existing accounts (and thus lengthens their credit history), and the control group as young adults who gain AU status on a newer account that does not. We use the same covariates and matching as in the first approach, and we also match on the AU account's credit limit, as a proxy for the sponsors' financial condition. Any remaining selection bias must arise through other characteristics of the shared credit history, rather than the binary choice of whether to grant AU status or the credit limit, because everyone in this sample gains an AU account and is matched based on the limit.[1]

[1] Although it is possible that AU sponsors strategically choose which credit facility to authorize based on account age, this choice would require knowledge that is more sophisticated than most consumers demonstrate. Survey evidence suggests most US consumers have a poor understanding of even the most basic mechanics of credit scoring. A 2021 myFICO survey shows that respondents were able to answer only 47% (those who self-reported as 'not knowledgeable') to 53% (those who self-reported as 'very knowledgeable') of multiple choice questions about how

Our first set of tests examines the effect of AU status on credit scores. Summary statistics show large differences in the average credit scores for those with AU status compared to those without AU status: at age 21, the difference is 108 points. To isolate the effect of AU status from that of other borrower characteristics, we employ our two difference-in-differences approaches. Using our extensive margin test, we estimate that gaining AU status increases a borrower's credit score by approximately 30 points. This increase is comparable to the credit score gap in the auto loan market between minority and non-minority borrowers (Butler et al., 2023), and larger than the effect of filing successfully for Chapter 13 bankruptcy (Dobbie et al., 2017). We confirm the effect using our intensive margin test that uses only AUs and compares those receiving long histories to those receiving short histories. Here, the estimated effect of receiving a longer history ranges from 22 to 42 credit score points. This result supports the view that the credit score increases are indeed due to the inherited credit history, rather than an artifact of selection into AU status.

Much of this increase stems from the way credit bureau systems treat AU accounts: borrowers inherit the full repayment history and age of the sponsor's account. On average, when gaining AU status, the reported length of the AU borrower's credit history increases by 2.5 years, and 4% of new AU borrowers appear to have credit histories that exceed their actual age. The credit score increase is significantly larger for borrowers with limited credit history. "Thin file" borrowers, i.e., those with one or fewer accounts in the prior year, experience a 33 to 45 point larger increase than their more established peers. AU borrower age also matters. Borrowers under 22 years old see credit score increases 10 to 25 points larger than those aged 23–25. These results are consistent with an information-based story, where the benefit of AU status is greatest when borrowers have little or no credit history of their own.

Our second set of empirical tests examines whether young adults have better access to credit after they gain AU status. On one hand, having a higher credit score should increase the

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credit scoring works, such as "What information is used to calculate your credit scores?" and true/false questions like "A missed payment is immediately removed from your credit report when you have paid the balance in full." This general confusion about credit scoring mechanisms makes strategic selection of accounts for AU purposes less plausible. See https://www.myfico.com/credit-education/blog/financial-literacy-survey.

AU's access to credit. On the other, if the higher credit score does not reflect true creditworthiness and lenders use additional information or adjust scores based on AU status, then we might expect minimal effects. We start by using our two difference-in-differences approaches to study access to credit cards. We find that young adults with an AU account addition see a significant increase in total credit card limits and approval rates for new credit cards that are not sponsored.

We next ask whether AUs gain greater access to credit in other markets. With credit cards, the consequences to lenders of making poor underwriting decisions may be relatively small because borrowers' credit limits tend to be modest. Moreover, credit card lenders may find accrued interest on carried balances and late fees to be profitable. But what about larger loans, such as those for automobiles or homes? We estimate that auto loan approval rates increase by about 2.7 percentage points and mortgage approval rates increase by about 2.9 percentage points after young adults gain AU status. Overall, these results show that the effect of AU status on credit access extends beyond credit cards to each of the major consumer credit markets.

Our third set of empirical tests examines whether the increases in credit scores and credit access for AU borrowers are warranted based on ex post performance as measured by subsequent delinquencies and credit score changes. They are not: AU borrowers are delinquent more often than non-AU borrowers *with the same credit score.* In the full sample, AU borrowers are 0.5 to 1.9 percentage points more likely to be delinquent in a given year, relative to a mean of 13%. The results are even larger among subprime borrowers and are robust to the rich set of control variables and matching approach. Importantly, the fact that AU borrowers have higher delinquency rates undermines alternative explanations for our previous findings that would posit positive (and unobservable) selection into AU status.

Our next tests focus on credit score evolution to assess whether the initial increase in an AU's credit score persists or reverses. Despite the fact that, on average, young borrowers' credit scores increase over time, on average, AUs' credit scores decrease by 5 to 12 points per year after gaining AU status, relative to their control group. However, the reversion in credit scores takes years, and we document a significant initial expansion in AU borrowers' access to credit, highlighting the consequential nature of AU accounts for young adults.

Finally, we consider the distributional consequences of including AU accounts in young adults' credit scores to assess whether AU accounts primarily enhance efficiency or perpetuate inequity. We sort the data into deciles based on ZIP code income levels. AU status rises sharply with income: only 6% of young adults in the lowest-income ZIP codes have AU status, compared to 27% in the highest-income ZIP codes. Sponsors may have relationships with prospective AUs (e.g., children) that allow them to act as delegated screeners or monitors, so AU status could convey true creditworthiness. But in practice, the evidence is more consistent with inequity: conditional on credit score, AU borrowers perform significantly worse than non-AU borrowers ex post. Ultimately, our findings suggest that this feature of the U.S. credit scoring system disproportionately benefits children from higher-income households.

Our paper makes several contributions to the literature. First, we contribute to the literature on the role of credit histories and credit scores in determining the allocation of credit. Several papers provide theoretical underpinnings for credit scores and information sharing among lenders as important tools for allocating credit effectively (e.g., Pagano and Jappelli, 1993; Chatterjee et al., 2023). Empirical studies document that credit histories and scores affect credit access, using settings such as bankruptcy flag removals (Musto, 2004; Gross et al., 2020; Dobbie et al., 2020) and credit score thresholds in mortgage lending (Bubb and Kaufman, 2014; Laufer and Paciorek, 2022). We add to this literature by documenting how an important institutional feature (the inclusion of AU accounts) affects credit scores, and through them, young adults' access to credit.

Given the importance of credit scores, a growing literature examines their accuracy and discusses equity considerations. Avery et al. (2012) combine credit scores with demographic information and conclude that scores do not produce a significant disparate impact based on race, ethnicity, or gender. Recent studies document that credit scores are less informative for disadvantaged groups due to data sparsity (Blattner and Nelson, 2024) and that non-traditional data sources can provide useful complementary information (Berg et al., 2020; Di Maggio and

Ratnadiwakara, 2025). Studies also document that machine learning models of creditworthiness can achieve greater accuracy than traditional credit scores (Khandani et al., 2010; Fuster et al., 2022), and that young borrowers would benefit from such models (Albanesi and Vamossy, 2024). We contribute to this literature by documenting how a specific underlying mechanism creates noise and misclassification in young borrowers' credit scores and distorts credit.

Most related to our study is the nascent literature on authorized user accounts. Brevoort et al. (2013) provide institutional background on AU accounts and show that they increase credit scores in a scoring model developed by Federal Reserve staff. In a similar vein, Bach et al. (2023) provide descriptive evidence that young adults with inherited credit histories have higher scores. In contrast, we use our credit bureau panel and two difference-in-differences approaches centered around AU account additions to directly estimate the effect of AU accounts on credit scores and access to multiple credit products. Importantly, our analysis of ex post default rates and credit score changes then sheds light on the merits and distributional consequences of including AU accounts in credit files. Closest to our study is a contemporaneous working paper from the Consumer Financial Protection Bureau (Blizard et al., 2025), which studies the fallout of AU status removals due to AU sponsors' financial distress and finds that former AUs' credit scores and access to credit decline. While these results mirror some of our findings, we see important advantages of our empirical design. Using AU account additions, rather than distress-induced removals, avoids biases that may arise due to family-level distress. Our study of AU account additions also ensures that our findings speak directly to the initial benefit and the long-term consequences of gaining AU status at a young age, which is likely particularly important to economists and policymakers.

Finally, our paper contributes to the growing literature on the intergenerational transmission of socioeconomic status, whether measured by wealth (Charles and Hurst, 2003), income (Chetty et al., 2014), education (Black et al., 2005), or in this case, by credit scores and access to credit. While a vein of research has studied ties between parent's access to credit and children's outcomes (Gaviria, 2002; Mazumder, 2005; Mayer, 2024), work by Ghent and Kudlyak (2016) was among the first to document the strong intergenerational correlation in credit scores.

We add to this literature by documenting an important mechanism through which parents can directly transfer a component of their credit score to their children, whether or not it is justified by fundamentals.

2. Institutional Background

The major consumer credit bureaus in the U.S. describe a credit score as "a simple-to-read number that can help creditors understand credit risk—the risk that they won't get repaid in full."[2] Credit scores are useful to lenders because they summarize and synthesize many dimensions of a person's creditworthiness into a single number. Although credit scoring models are proprietary, the developers and credit bureaus provide guidance on the most important factors influencing scores. For example, FICO explains that their scores are calculated using five main categories of credit report information (with approximate weights): Payment History (35%), Amounts Owed (30%), Length of Credit History (15%), Credit Mix (10%), and New Credit (10%).[3] Credit scores typically range from 300 to 850, with higher scores indicating better credit quality.

Authorized user accounts are cases where a primary borrower adds a second person to a credit facility like a credit card, so that the second person (the AU) can use the card, but all the repayment responsibility remains with the primary borrower. AU accounts are different from joint accounts, where for example, two borrowers co-sign a loan and are both responsible for the payments. Importantly, despite the fact that AUs are not responsible for repayment, AU account information like account age, credit limit, and repayment history is added to the AU's credit file. The addition of this information can then affect credit scores through factors like Payment History, Length of Credit History, and Credit Mix. For parent-to-young adult AU relationships, where the

[2] See Credit Score Basics: Everything You Need to Know (https://www.experian.com/blogs/ask-experian/credit-education/score-basics/understanding-credit-scores/).
[3] See What's in my FICO Scores? (https://www.myfico.com/credit-education/whats-in-your-credit-score). We note that the credit score we use throughout the paper is the VantageScore, which is the second most used credit score. For a similar breakdown of VantageScore factors, see What are the factors that go into VantageScore? (https://www.chase.com/personal/credit-cards/education/credit-score/vantagescore-ranges-explained). VantageScore was developed by the three major credit bureaus to rival FICO scores; it has the same score range and is very similar, which led FICO to sue (unsuccessfully) the credit bureaus for producing such a similar product.

parent often has a longer credit history and the young adult often has a thin credit file, we might expect the transfer of this information to improve the young adult's score, although the magnitudes remain an important empirical question.[4]

Historical factors and regulations have laid the groundwork for why credit bureaus include AU accounts in credit files and credit scores. Consumer credit expanded significantly in the 1950s-1960s with the widespread adoption of credit cards and the AU role emerged as a convenient way for primary account holders (typically men at the time) to permit spouses to make purchases on the card. However, women during this time often reported difficulty accessing credit on their own because the credit history of their shared accounts with their husband was frequently reported to the credit bureaus in only their husband's name. The Federal Reserve Board took this issue into account when implementing the broader Equal Credit Opportunity Act of 1974 through its Regulation B. The new regulation required starting in 1975 that lenders report AU accounts to the credit bureaus in both the parties' names. Moreover, the regulation required that lenders consider in any assessment of creditworthiness any shared accounts with spouses, including both AU accounts and joint accounts, reinforcing shared accounts' inclusion in credit scoring. In complying with Regulation B, lenders have historically provided information on all AU accounts to the credit bureaus and have not distinguished spousal from non-spousal accounts. Hence, the credit bureaus include all types of AU accounts when computing credit scores.

For young adults, who may have limited credit histories or little experience building credit independently, achieving a high credit score can be challenging. Without an established credit history and quality, these borrowers may face higher borrowing costs or difficulty accessing credit at all. In such cases, becoming an AU on a family member's account can provide a shortcut to establishing a positive credit history. Although some lenders may recognize that credit history gained through AU status may not reflect the borrower's true credit quality or repayment habits, it is an empirical question whether or not AU status confers a meaningful increase in credit access.

[4] Consistent with the added information generally being positive, we note that any subsequent delinquencies by primary borrowers on the account are not passed through onto the AU's credit file, as discussed in Blizard et al. (2025).

3. Data and Methods

To conduct our empirical analysis, we build a nationally representative panel dataset of 18- to 25-year-olds in the US who participate in credit markets. We use data from a major credit bureau to track credit inquiries, usage, and outcomes. In this section, we discuss the data sources, sample construction, summary statistics, and our coarsened exact matching methodology.

3.1 Data Sources

This paper uses a dataset of anonymized individual credit bureau records. Any individual who has a credit account from a lender reporting to the credit bureaus (mortgage, auto loan, credit card, etc.), or who previously had an account that closed within the last seven years, has a credit history. Our data consist of a 1% representative panel of all U.S. residents with a credit history and Social Security number.

The 1% sample is constructed using Social Security numbers ending in an arbitrarily chosen final two digits. This procedure produces a random sample because the Social Security Administration assigns the last four digits of Social Security numbers sequentially, regardless of location. The panel tracks individuals over time and allows people to enter and exit at the same rate as the target population, ensuring that the sample remains representative. This sampling method closely follows that of the Federal Reserve Bank of New York Consumer Credit Panel (see Lee and Van Der Klaauw, 2010). The dataset is based on credit files as of December 31st of each year and includes annual observations for approximately 2.5 million people per year from 2004 to 2020.

These credit bureau data provide a complete credit history for each individual, including their credit score, total debt, debt by category (mortgage, auto, credit card, etc.), past due debt, new sources of credit opened, and "hard" credit inquiries. These credit inquiries occur when a borrower applies for credit, and the lender checks their credit report. The data also provide the individual's age and the ZIP code in which they live. We supplement our credit bureau data with additional information from the American Community Survey. We use these data to measure per capita income and other demographic characteristics at the ZIP code level. These variables serve as important controls in our empirical tests. All variables are defined in Appendix Table A.1.

3.2 Sample Construction and Summary Statistics

To construct our main analysis sample, we start by including all person-years in the credit bureau data where the person is between 18 and 25 years old. This approach excludes the 0.59% of person-year observations where the reported age is less than 18 years old and tracks people until they reach age 25. We then exclude the small number of individuals who did not have active AU status during the sample period but were an AU on an account before our data begin (1.1% of the sample). Lastly, in our main analysis, we exclude individuals who enter the data already as AUs, representing about 11% of our sample. We exclude these individuals because we cannot observe them prior to their AU account and hence cannot study them in our difference-in-differences framework. Summary statistics in Appendix Table A.2 show that these "Always AU" individuals enter the data with higher credit scores and come from higher-income ZIP codes than the typical young adult. Although we do not use them in our main analysis, we do include the Always AU group when providing evidence on the prevalence of AU status and its correlation with ZIP code characteristics in Figures 1 and 8. Our main analysis sample covers the period 2004 to 2020 and includes about 787,000 unique individuals and 3.56 million person-year observations.

Table 1 Panel A reports summary statistics for the full sample. Columns 1-6 present the mean, standard deviation, 10th, 50th, and 90th percentiles, and the number of observations. The average person in the sample has a credit score of 609 and has $11,560 in total debt. 15% of borrowers are delinquent on a credit account, and 4% are listed as AUs on other people's credit accounts (e.g., those of parents). This 4% share is lower than the share reported in Figure 1 because, as mentioned above, we exclude individuals who enter the data already as AUs.

[Insert Table 1 Here]

3.3 Matching Methodology

Our empirical tests use two sources of variation to assess the impact of AU status. First, we compare those who gain AU status after entering the credit bureau data (Later AUs) to those who never gain AU status (Never AUs). Second, we conduct an intensive margin analysis, where we compare Later AUs who receive a long credit history through the AU account to Later AUs who receive a short credit history.[5] For each of these approaches, we conduct baseline versions of the test using the full sample, followed by matched versions of the test.

We use coarsened exact matching (CEM) to form our matched samples. For the extensive-margin analysis, we match Later AUs to Never AUs using characteristics measured when individuals first appear in the credit bureau data. Specifically, we include ZIP-code income, total debt excluding AU debt, and credit score, and we exactly match individuals on their entry age and the calendar year they enter the sample. For the intensive-margin analysis, we match Later AUs receiving long credit histories to those receiving short histories using the same set of characteristics, while additionally matching on age measured just before treatment and on the credit limit of the AU account, which may proxy for family wealth. For all of our matched sample analyses (and the summary statistics below), we follow the CEM practice of reweighting the non-treated observations within each matched cell to reflect the treated-control composition of that cell.

Table 1 Panel B presents summary statistics comparing the full sample of Later AUs vs. Never AUs (columns 1-3), as well as the matched sample of Later AUs vs. Never AUs (columns 4-6). The statistics show that after matching, normalized differences fall to no more than 0.08 in absolute value, and balance improves for credit score, age, debt levels, and delinquencies.

Table 1 Panel C presents summary statistics comparing Later AUs receiving long credit histories vs. short credit histories for the full sample (columns 1-3) and matched sample (columns 4-6). The statistics show improved balance in pre-treatment debt usage. Overall, the summary statistics show that our CEM approach effectively eliminates the observable differences between

[5] We define a long credit history added as one that predates the start of the person's own credit history, and thus lengthens their credit history.

the treated and control units. This approach mitigates the influence of any outliers and reduces the dependence on modeling choices and the extrapolation that takes place in linear regressions.

4. Empirical Results

4.1 Authorized User Accounts and Credit Scores

In this section, we study the impact of AU accounts on young adults' credit scores. We do so by examining how the addition of an AU account to young adults' credit histories affects their scores using two difference-in-differences designs. Our specifications take the form:

$$Y_{i,z,s,t} = \beta_1\, Treated_i\ X\ Post_{i,t} + \beta_2\, Borrower\ Controls_{i,t-1} + \beta_3\, ZIP\ Controls_{z,t-1} + \delta_i + \gamma_{s,t} + \epsilon_{i,z,s,t} \quad (1)$$

where subscripts *i*, *z*, *s*, and *t* represent the person, ZIP code, state, and year, respectively.

Our first difference-in-differences approach compares young adults who experience a new addition of an AU account between the ages of 19 and 25 (the treated group), to young adults who never have an AU account before age 25 (the control group). Our second difference-in-differences approach focuses on the intensive margin, by comparing young adults who receive a long credit history through an AU account (treated) to those who receive a short credit history through an AU account (control). We label the indicator variables denoting treatment for these two approaches as $AU\ Treated_i$ and $Long\ History\ Treated_i$, respectively.

The dependent variable, $Y_{i,z,s,t}$, in the current tests is the person's credit score (later tests also examine measures of credit access). The independent variable of interest is $AU\ Treated_i\ X\ Post_{i,t}$ (or $Long\ History\ Treated_i\ X\ Post_{i,t}$), which is an indicator for the treated group interacted with an indicator for observations after the AU status is added. We note that these $Treated_i\ X\ Post_{i,t}$ terms equal one for all person-years after the AU account is added, even if the AU account is later removed from the young adult's credit record. This approach has three advantages. First, by focusing on the long-run effects of AU account additions, the approach provides the most relevant estimates to economists and policymakers considering the consequences of allowing such accounts in credit scoring. Second, the approach avoids using time-series variation in AU status stemming from AU account *deletions*, which may be endogenously related to family-level financial distress. Finally, the approach makes our estimates conservative, in the sense that we consider AU account additions that turn out to be short-lived ex post as treatments for the remainder of young adulthood. This prevents our estimates from reflecting only the successful ongoing AU relationships. In later robustness tests, we show that our main results are similar if we instead allow the treatment variable to turn off following AU account deletions.

We include a robust set of control variables. $Borrower\ Controls_{i,t-1}$ and $ZIP\ Controls_{z,t-1}$ are vectors of lagged time-varying borrower characteristics (including debt usage and age indicators) and ZIP code characteristics, respectively. The specification also includes individual and state-year fixed effects, denoted by δ_i and $\gamma_{s,t}$, respectively. These fixed effects control for any time-invariant characteristics of the borrower or changes in economic conditions across states over time. Because we are identifying the effects of AU status as a within-individual effect, alternative explanations for our findings must be independent of individuals' innate characteristics, including family background, prior education, and any other lived experiences. Standard errors are clustered by individual. Furthermore, to address any concerns that staggered treatment timing across treated individuals may bias two-way fixed effects estimates, we use the Callaway and Sant'Anna (2021) estimator to estimate treatment effects and test for pre-trends in the figures corresponding to the tables.

Table 2 presents the results. The baseline difference-in-differences test in Column 1 shows that young adults' credit scores increase by 31 points following the addition of an AU account, compared to the control group who do not have an AU account addition prior to age 25. Column 2 presents the results for the same test, except using the sample constructed through CEM. The matched design also permits the inclusion of cohort-year fixed effects, where cohorts are defined by CEM cells, which we include for additional robustness. The CEM results are very similar to the baseline results, yielding an estimated effect of 30 points. The economic magnitude of these estimates is striking: the impact of AU accounts on credit scores is similar to the magnitude of successfully filing for Chapter 13 bankruptcy protection (Dobbie et al., 2017).

Columns 3 and 4 turn the focus to the intensive margin, by comparing young adults who receive a long credit history through an AU account addition to their peers who also have an AU account addition but receive a short credit history. The results in Column 3 show that the addition of AU accounts with long histories has a sizeable positive effect (42 points) on credit scores. The CEM results in Column 4 continue to show a large effect (22 points). These intensive margin tests on the CEM sample draw particularly tight comparisons between treated and control units: they compare young adults receiving AU accounts in the same calendar year and at the same age, and are matched on pre-treatment credit scores, non-AU debt balances, and ZIP-code income. In addition, the match includes the AU account credit limit, which proxies for the primary account holder's financial capacity. Overall, the tests in Table 2 provide strong evidence that AU account additions lead to large increases in young adults' credit scores, and that the effect is linked to the length of credit history added.

[Insert Table 2 Here]

The identifying assumption underlying our difference-in-differences approaches is that, absent the treatment, credit scores would have trended similarly for young adults in both the treatment and control groups. Although it is not possible to test this assumption directly, we can examine the trends prior to treatment and the dynamics of the effects we document. To do so, we implement a dynamic version of our difference-in-differences test using the Callaway and Sant'Anna (2021) estimator to address potential biases from two-way fixed effects in staggered adoption settings. Figure 2 presents the bias-adjusted estimates of the effect from three years before to five years after treatment. Panels A and B show results for the extensive margin comparison (Later AU vs. Never AU) using the full sample and matched sample, respectively. Panels C and D show results for the intensive margin comparison (Long vs. Short History Added), again using the full and matched samples. The figures show relatively flat pre-trends, followed by a large and immediate jump in credit scores for the treated group in the year of AU account addition. This large jump in credit scores provides strong evidence that AU account additions cause increases in young adults' credit scores.

[Insert Figure 2 Here]

We next explore the cross-sectional variation in the effect of AU account additions. We examine variation in the main effect based on the amount of information available about the borrower, measured based on the breadth of the borrower's credit file and their age. To conduct these tests, we define borrowers as having thin credit files if they have one or fewer existing credit accounts, and we define borrowers as particularly young if they are 21 and younger. We report the results of the triple-differences tests in Table 3.

The results in Table 3 Panel A show that the effect of AU account additions is significantly larger for borrowers with thin credit files. For example, the point estimates in Column 1 indicate that while a borrower with a thick credit file might expect a 15-point increase in their credit score following an AU account addition, a borrower with a thin file could expect an additional 33-point increase (or 48-point total increase) in their credit score. The results in Columns 2 through 4 confirm that this pattern holds when using CEM and when studying the intensive margin.

Table 3 Panel B reports the tests based on borrower age. We find that the effect of AU account additions is significantly larger for particularly young borrowers. This pattern holds across each of our four specifications, with the estimated additional effect for young borrowers ranging from around 10 to 25 points. The cross-sectional patterns documented in Table 3 are broadly consistent with an information-based explanation: AU account additions have the largest impact on the credit scores of young adults about whom the credit bureaus otherwise know the least.

[Insert Table 3 Here]

Overall, the results in this section document a substantial positive effect of an AU account addition on credit score, which is even larger when the AU account has a long history or when the young adult is a relatively opaque borrower. Although this positive effect on credit scores may not be surprising given that credit scoring algorithms use the length of history when computing scores, the magnitudes are striking and economically meaningful. Our tests in the following sections examine how AU account additions affect young adults' access to credit and whether the large increases in credit scores are warranted based on borrowers' subsequent financial performance.

4.2 Authorized User Accounts and Access to Credit

The tests in this section examine whether AU account additions affect young adults' access to credit. We start by examining access to credit cards. We then examine broader access to credit across products such as auto loans and mortgages. If lenders in these markets rely heavily on credit scores, we might expect the large credit score increases following AU account additions to significantly expand borrowers' access to credit. However, if lenders are less dependent on credit scores or if they adjust them based on other information such as AU status, then we might expect to see smaller effects on credit access following AU account additions. Ultimately, this is an empirical question, which we tackle in this section.

We use the same difference-in-differences approach described above and formalized in Equation (1) to study the effect of new AU account additions on young adults' access to credit cards, which we measure based on credit limits and credit card approval rates. Table 4 presents the results for credit card limits. Column 1 shows that AU account additions lead to an increase in total borrowing limits across all credit cards of approximately $6,200. This increase in limits is large, at more than twice the unconditional average limit of $2,226, although we note that some of this increase is mechanical due to the limit on the AU sponsor's card contributing to the total. Column 2 reports a similar estimate of around $6,030 using the CEM sample. The results in Columns 3 and 4 also document a significant increase in limits along the intensive margin.

[Insert Table 4 Here]

Figure 3 presents the dynamic properties of the effect on credit limits using the estimator proposed by Callaway and Sant'Anna (2021). Panels A and B show the results for the extensive margin comparison (Later AU vs. Never AU) for the full and matched sample, respectively. We see no meaningful pre-trends in credit limits prior to AU account addition. Panels C and D show the results for the intensive margin comparison (Long vs. Short History Added), where we see a *negative* pre-trend in limits for the treated group. In all cases, the figures show a large and immediate increase in total credit card limits as the AU account is added.

[Insert Figure 3 Here]

We next examine approval rates for borrowers seeking to open new credit cards without an account sponsor. To conduct this test, we restrict the sample to person-years in which the borrower applies for a credit card, which we identify based on the "hard" credit inquiry from a credit card lender that appears on the person's file when the lender checks their score. We measure access to non-AU credit cards using the indicator variable, *Non-AU Credit Card Approval*, which equals one if the person's number of non-AU credit cards increases during the year. This approach follows several papers that use credit bureau data to construct and validate similar measures of credit access (Akey et al., 2018; Bhutta and Keys, 2016; Brown et al., 2019; Butler et al., 2023). We note that for our approval tests, we include in the specification the indicator variable for being a treated individual, rather than individual fixed effects. This adjustment preserves the difference-in-differences design, but avoids requiring individuals to have multiple years (i.e., observations) where they shop for credit. It is important not to impose this requirement, because it would exclude relevant observations and could introduce dependencies between approvals on earlier shopping attempts and the likelihood of observing future shopping attempts.

Table 5 presents the results. The point estimate in Column 1 shows that young adults' approval rates for non-AU credit cards increase by 3.4 percentage points following AU account addition. The CEM results in Column 2 are similar, with a point estimate of 4.1 percentage points. These estimated effects are economically important, representing nearly a 10% increase in approvals relative to the unconditional approval rate for this sample of 42.6%. Columns 3 and 4 report consistent evidence from the intensive margin: young adults receiving a long history through an AU account see an increase in approvals of between 6.7 and 4.3 percentage points relative to their peers receiving a short history through an AU account, respectively. These findings are consistent with the credit score effects of AU accounts documented in Section 4.1 carrying through to credit card underwriting decisions (which are typically automated) in an impactful way.

[Insert Table 5 Here]

In Figure 4, we again plot the dynamic coefficients using the Callaway and Sant'Anna (2021) estimator. Panels A and B show the results for the extensive margin; Panels C and D show the results for the intensive margin. None of the figures show meaningful pre-trends in non-AU credit card approvals prior to treatment. In all cases, there is a sharp increase in approval rates for the young adults' own credit cards once the AU account is added, with the effects persisting for two to three years. The lack of pre-trends and sharp increase in approvals is consistent with a treatment effect of AU status, rather than differing economic trajectories for the treated and control groups.

[Insert Figure 4 Here]

Our next tests examine whether the expansion in credit we document for credit cards extends to broader credit markets such as the auto loan market and mortgage market. On the one hand, auto and mortgage lenders' underwriting processes also rely on credit scores, suggesting AU accounts could continue to expand access to credit in these markets. On the other hand, auto and mortgage lending are generally less automated than credit card lending, which could allow lenders to incorporate more information beyond scores into their decisions. Auto and mortgage loans are also larger, less frequent, and involve collateral, all of which could lead to differences in underwriting practices compared to the credit card market.

Table 6 Panel A presents the tests examining auto loan approvals. The point estimates in Columns 1 and 2 show that young adults' approval rates increase by 2.7 percentage points following AU account addition. These estimated effects represent nearly a 4% increase in auto loan approvals relative to the average approval rate for this sample of around 62%. The intensive margin results in Column 3 confirm that young adults receiving a long history see an increase in auto loan approvals relative to those receiving a short history. The CEM version of the intensive margin test in Column 4 has a smaller sample and shows a positive but statistically insignificant point estimate.

[Insert Table 6 Here]

Figure 5 presents the dynamics of the effect on auto loan approvals using the Callaway and Sant'Anna (2021) estimator. Panels A and B show the results for the extensive margin (unmatched and then using CEM), while Panels C and D show similar results for the intensive margin test. None of the figures show significant pre-trends in approvals prior to treatment. In each of the four figures, there is a sharp increase in auto loan approvals once the AU account is added, with the effects persisting for several years. The lack of pre-trends and sharp increase in approvals is consistent with AU status (and the corresponding increase in credit scores) having a significant impact on young adults' access to credit in the auto loan market.

[Insert Figure 5 Here]

In Table 6 Panel B, we examine whether AU status affects young adults' access to mortgage credit. The point estimates in Columns 1 and 2 show that mortgage approval rates increase by about 2.8 percentage points following AU account addition.[6] Columns 3 and 4 examine the intensive margin based on the length of credit history added and also show positive effects, with approval rates increasing by 3.3 to 4.7 percentage points.

We examine the dynamics of the mortgage approval effects in Figure 6. Panels A and B show the results for the extensive margin, while Panels C and D examine the intensive margin. In Panels A through C, we do not see any significant evidence of pre-trends. In Panel D, there is a slight *negative* pre-trend. In each panel, we see increases in mortgage approvals following treatment. We also note that the estimates for the intensive-margin tests are less precisely estimated, due to the smaller sample sizes that come from fewer young adults searching for this type of credit.

[Insert Figure 6 Here]

Overall, the results in this section show that AU account additions lead to large increases in young adults' credit card limits and access to their own (non-AU) credit cards. The expansion in credit access extends beyond the credit card market to the auto loan market. We also find some evidence of a positive effect on young adults' access to mortgage credit.

4.3 Robustness Checks

In this section, we conduct three important tests to confirm the robustness of our results so far. First, we replicate our main results (i.e., the effect on credit scores, credit card approvals, auto

[6] This estimate is large relative to the low average approval rate for these individuals of 19%. We note that mortgage approval rates computed based on credit bureau inquiries are typically much lower than those computed based on data from the Home Mortgage Disclosure Act. The difference arises because lenders only need to report formal mortgage applications where an underwriting decision is rendered (or the application is withdrawn) to the HMDA database. In contrast, credit bureau inquiries capture a broader definition of borrowers' search for credit: having lenders pull their credit score due to potential interest in taking out a mortgage.

loan approvals, and mortgage approvals) using an alternate definition of the AU treatment variable. The alternate treatment variable is simply an indicator for whether the borrower is an authorized user on an account during the current year. We find similar results using this definition of treatment (see Appendix Table A.3). Second, we replicate our main results after excluding all person-years where the credit bureau estimates the person is married (this variable is available from 2010 onward). The results, reported in Appendix Table A.4, remain similar to our main results. Lastly, we replicate our main results after restricting the sample to the years 2011-2019. The results, reported in Appendix Table A.5, confirm that none of our findings are driven by either the 2008 Financial Crisis or the onset of the COVID-19 pandemic.

4.4 Do Authorized Users Live Up to the Credit Score Increase?

Having shown that AU status increases a borrower's credit score and access to both revolving and non-revolving credit, we ask in this section whether these increases are warranted? In other words, we ask whether AU borrowers prove themselves to be as creditworthy as their scores suggest? To address this question, we examine two types of ex post outcomes that reveal creditworthiness: default rates and future movements/reversions in credit scores.

We start with a simple plot of the data in Figure 7. We create 20 equal-sized bins of AU borrowers based on credit score at the start of the year, and then 20 similar bins for their non-AU counterparts.[7] We then plot the bin average rate of severe delinquencies (having one or more accounts that are 90 or more days past due) on the vertical axis, against the bin average credit score at the start of the year on the horizontal axis. If credit scores accurately reflect default risk across the two groups, the bins of the AU and non-AU borrowers should overlap directly. Figure 7 shows close overlap for the high credit score bins (e.g., those with scores over 700). However, for the lower credit score bins, the delinquency rates of AU borrowers are systematically *higher* than their non-AU counterparts. The differences are large: at a credit score of about 560, AU borrowers are

[7] For the tests in this section, we measure AU status based on whether the borrower was an authorized user on an account as of the start of the year (i.e., as of December 31st of year *t-1*).

delinquent at a rate of around 39%, compared to a 23% delinquency rate for non-AU borrowers. Although this is a simple plot of the data, the striking pattern cuts against the idea that AU borrowers are as creditworthy as their higher scores would suggest.

[Insert Figure 7 Here]

We formalize this comparison with the regressions we report in Table 7. The dependent variable is an indicator for severe delinquencies of 90 or more days past due. As in prior tests, we control for the borrower's non-AU debt-to-income ratio, total non-AU debt, time-varying ZIP code demographics, borrower age indicators, and state-year fixed effects. We now also include a granular set of indicator variables to denote each 10-point credit score bin ranging from 500 to 850 (with an additional bin for scores below 500). The rationale for this design is to examine whether, conditional on their credit score, AU borrowers default at different rates than their non-AU counterparts. If default rates diverge, it suggests that AU accounts distort credit scores across groups.

Table 7 Panel A presents these tests for the full sample (Panels B and C examine the prime and subprime samples separately). The results in Columns 1 and 2 show that for the full sample, young adults with AU status are about 0.5 to 0.8 percentage points more likely to have a serious delinquency than their non-AU counterparts, conditional on credit score and the control variables. This effect represents roughly a 5% increase in delinquencies relative to the average delinquency rate of 13.2% in this sample. Columns 3 and 4 report the intensive margin tests comparing young adults who receive long vs. short credit histories. These results show that the individuals who receive the largest increase in credit scores (through long histories) underperform their (high) scores by the largest degree: AU borrowers receiving long histories are 1.7 to 1.9 percentage points more likely to default conditional on credit score and the controls.

Panels B and C of Table 7 repeat the analyses from Panel A, except restricting the sample to prime borrowers (credit scores of 620 or higher) and subprime borrowers (credit scores below

620), respectively. The results in Panel B show that the same patterns from the full sample – higher delinquency rates conditional on scores for those with AU status, and especially for those receiving long histories – hold in the prime sample as well, although with slightly smaller magnitudes. The results in Panel C show that these patterns hold with even larger magnitudes in the sample of subprime borrowers.[8]

[Insert Table 7 Here]

So far, we have shown that AU status corresponds to an increase in credit scores, an increase in access to credit, and higher subsequent rates of default, especially for subprime borrowers. Taken together, we interpret this as evidence that AU status inaccurately inflates borrowers' apparent creditworthiness. We next ask whether these seemingly inflated credit scores revert over time? A documented reversion could be informative on two fronts. First, it would provide further evidence (complementing the evidence from defaults) that the initial increase in credit scores due to AU status is not fully warranted in the long run. And second, a reversion in scores could explain why some of the effects we document on credit access persist for several years and then dissipate.

Table 8 reports our tests for credit score reversion. In Panel A, the dependent variable is an indicator for the individual's credit score decreasing during the year.[9] The results in Columns 1 and 2 show that borrowers with AU status at the start of the year are 7.4 to 7.7 percentage points more likely to experience a credit score decline than their counterparts without AU status. This effect represents a 29% increase in the likelihood of a credit score decline, relative to the unconditional probability of a credit score drop in this sample of 36.7%. Columns 3 and 4 present

[8] A potential concern is that Always AUs (individuals who entered the data as AUs) may be less likely to underperform than individuals who are added as AUs later. However, in Appendix Table A.6, we show that the results remain similar if we include Always AUs in the test.

[9] We note that for the analyses in Table 8, we exclude the year of AU account addition from the tests, in order to avoid mechanically recapturing the initial credit score increase (i.e., lack of a decrease) during that year.

the intensive margin tests, which show that young adults receiving long AU histories are even more likely than those receiving short histories to experience a subsequent decline in credit scores. In Panel B, we confirm that these patterns hold if we measure credit score movements based on simple changes (i.e., first differences) in credit scores during the year. The results in Table 8 provide evidence of partial credit score reversion following AU account additions, particularly among individuals who inherit longer credit histories.

[Insert Table 8 Here]

Overall, the results in this section show that young adults with AU status do not "live up" to their higher credit scores. Young adults with AU status are significantly more likely to default than their non-AU peers with similar credit scores. Over time, this disconnect between credit scores and underlying creditworthiness is reflected in outcomes and AU borrowers' credit scores revert to lower levels.

5. Implications for Inequality

Our tests, which primarily utilize within-borrower time-series variation in AU status and control for important borrower characteristics, should be interpreted in a ceteris paribus context. We are trying to remove from the analysis the confounding determinants of who gets AU status. To the extent that we are successful, holding all else equal, our results indicate that AU status increases credit scores and credit availability, but that AU borrowers ultimately become delinquent at higher rates relative to their credit scores. But if we relax our attempts to hold all else equal, we can learn about who becomes an AU borrower and the distributional consequences of the practice.

An important dimension along which differences may be visible is family wealth. Wealthy parents may have better credit histories and greater financial sophistication, which could increase their likelihood of "lending" their credit history to their children, compared to less wealthy parents. Our data do not allow us to connect parents and children directly, however, we do observe where the borrowers live. We can then correlate the prevalence of AU status with socioeconomic characteristics such as ZIP code income levels. For this exercise, we expand the data to include all young adults who received AU status, including those who enter the data already as AUs, and we measure ZIP code based on the young adults' first appearance in the data in order to proxy for family socioeconomic status.

Figure 8 Panel A presents a binned scatter plot of AU account prevalence for 21-year-olds in our data on the vertical axis, against average income in the ZIP code where they come from on the horizontal axis. The visual relationship between ZIP code income and AU prevalence is nearly a straight line. For ZIP codes in the bottom half of the income distribution (below about $25,000 per capita), fewer than 10% of 21-year-olds have AU status. In contrast, for ZIP codes in the top decile, more than 25% of 21-year-olds have AU status.

[Insert Figure 8 Here]

In recent years, the issue of "credit invisibility" – the fact that about 10% of US adults have no credit history – has drawn significant attention from policymakers due to the wide-ranging use of credit scores across various markets. In Figure 8 Panel B, we examine the potential role of AU accounts in disparities in "credit visibility" between young adults from high- versus low-income households. Specifically, we plot the fraction of 21-year-olds in our data who *only have a credit file due to an AU account* against the average income in the ZIP code they came from. The plot shows that AU accounts generate about 9% of the credit visibility of young adults in the highest income ZIP codes, compared to just over 1% in the lowest income ZIP codes.

Our final point is to discuss the potential broader implications of our findings given that credit scores are used in many settings, from credit markets, to labor markets, to insurance markets, to name only a few. We start by providing, in Figure 8 Panel C, a simple overlay of the histograms of the starting credit scores (upon entering the data) for two groups: young adults whose credit file is created *only* due to an AU account, and young adults that entered the data without an AU account.[10] The histograms show massive differences, with the AU-entry distribution centered around scores in the low 700s and the non-AU-entry distribution centered around scores in the low 600s. Although a meaningful portion of this variation could be correlated with young adults' otherwise unobservable types in a way that is useful to decision-makers in various markets, the raw magnitudes are striking given that the young adults in the AU-entry group have not yet demonstrated any creditworthiness of their own.

Of course, providing precise point estimates of the magnitude of the AU advantage in each of the myriad settings in which credit scores are used is beyond the scope of our paper. However, we can provide some suggestive evidence on this front by using back-of-the-envelope calculations that draw on the extant literature's estimated elasticities of prices/outcomes in various markets to credit scores. To do this in a conservative manner, we use our point estimates from Table 2 showing that AU account additions lead to 30-point increases in credit scores after controlling for a rich set of covariates and using CEM. We then multiply this 30-point increase with the elasticities/coefficients found in several well-conducted studies.

In the mortgage market, regression estimates from Gurun et al. (2016) show that a one-point increase in credit scores corresponds to a 1.1 basis point lower interest rate, implying that the 30-point advantage could reduce a borrower's rate by 33 basis points. This AU advantage would be worth about $13,265 in present value terms for a typical $350,000 30-year fixed rate mortgage. In the auto loan market, Butler et al. (2023) estimate that a one-point increase in credit score corresponds to a 1.9 basis point lower interest rate, implying an AU advantage of 57 basis points which would be worth about $340 in present value terms for a typical $25,000 5-year auto loan. In the labor market, Ballance et al. (2020) document that following state-level bans on credit checks in hiring decisions, employment increased by 5% in low credit score census tracts compared to high credit score tracts (which had average credit scores about 100 points higher). While less direct, these results suggest that a 30-point credit score advantage could increase

[10] For the clarity of the histogram, we exclude the 6% of individuals that enter the data with both an AU account and a non-AU account in their first year, although we note that this group also has high starting scores.

employability by roughly 1.5% in a labor market with credit checks. Finally, recent research on home insurance premiums by Blonz et al. (2025) estimates that each one-point increase in credit score reduces annual premiums by roughly \$3 per year, suggesting a potential AU advantage of around \$90 per year in the home insurance market.

Although these back-of-the envelope calculations are simple and require assumptions, the takeaway is clear: a credit score boost of 30-points is associated with significant benefits in many economic settings. These calculations underscore the importance and broad implications of our findings. The inclusion of AU accounts in credit scoring institutionalizes the intergenerational transfer of economic advantages in important settings, with the primary beneficiaries being children from wealthier households.

6. Conclusion

In the U.S. credit system, authorized user accounts are included in credit bureau files and credit scoring. AU borrowers inherit the credit history of the authorized account, despite the fact that they are not ultimately responsible for repayment. By "borrowing" the credit history of the primary account holder, these AU borrowers can establish credit histories that extend well beyond their own. We show that individuals who become AUs see an increase in their credit scores of roughly 30 points – an increase caused by the track record of the account sponsor, rather than the AU's own credit activities.

This credit score increase has consequences. AU borrowers get access to more credit, both as authorized users and independently on their own accounts. They have higher approval rates for new credit cards, auto loans, and mortgages. However, our research shows that this increased access to credit is somewhat unwarranted. AU borrowers default significantly more than a borrower with the same credit score, but who achieved the score "naturally." In other words, the borrowed credit histories systematically inflate credit scores relative to true credit quality.

Although AU status causes credit scores to increase initially, they revert over time as the borrower's true credit quality becomes apparent. Meanwhile, these AU borrowers have gained access to credit that their counterparts without AU status did not. This unearned access to credit raises concerns about equitable access to credit markets, as AU status is neither ubiquitous nor randomly allocated. There is a monotonic increase in young adults' probability of being an AU as a function of the average income in the ZIP code they came from. Our findings, therefore, have implications for our understanding of not only the efficiency of the credit scoring system, but also its fairness.

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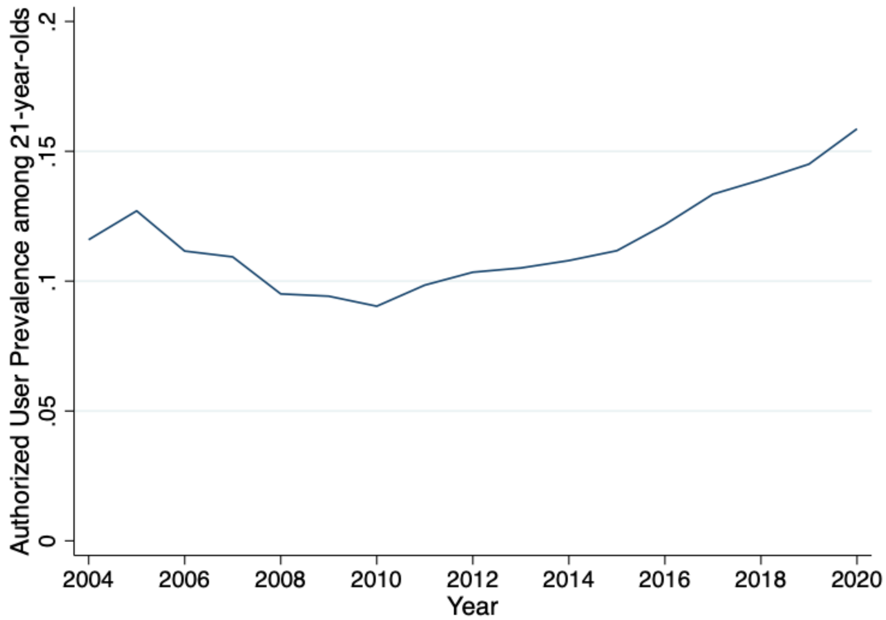

Figure 1: Authorized User Prevalence Over Time

This figure plots the percentage of 21-year-olds that have authorized user accounts over our sample period. The statistics are calculated using credit bureau data from 2004 to 2020.

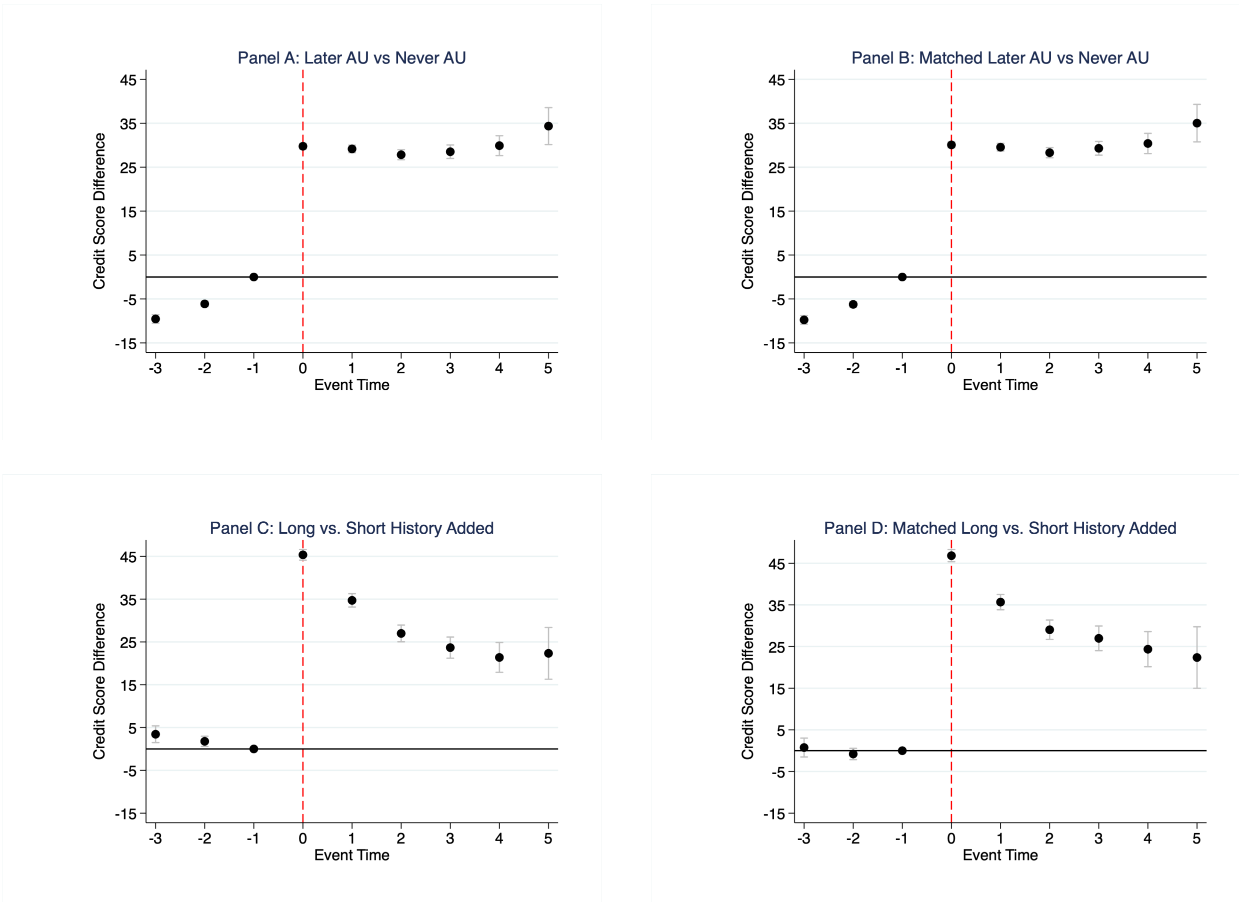

Figure 2: Effect of Authorized User Addition on Credit Scores

This figure plots the coefficients from a difference-in-differences specification examining the impact of authorized user account addition on credit scores. In Panels A and B, the control group is individuals who never received AU status. In Panels C and D, the control group is individuals who were added as AUs but did not experience an increase in the length of their credit histories as a result. We plot coefficients from three years prior to AU addition to five years after. The specification uses the Callaway and Sant'Anna (2021) estimator, including borrower- and ZIP-code-level controls, as well as individual and year fixed effects. Coefficients are plotted with 95% confidence intervals, with standard errors clustered at the individual level.

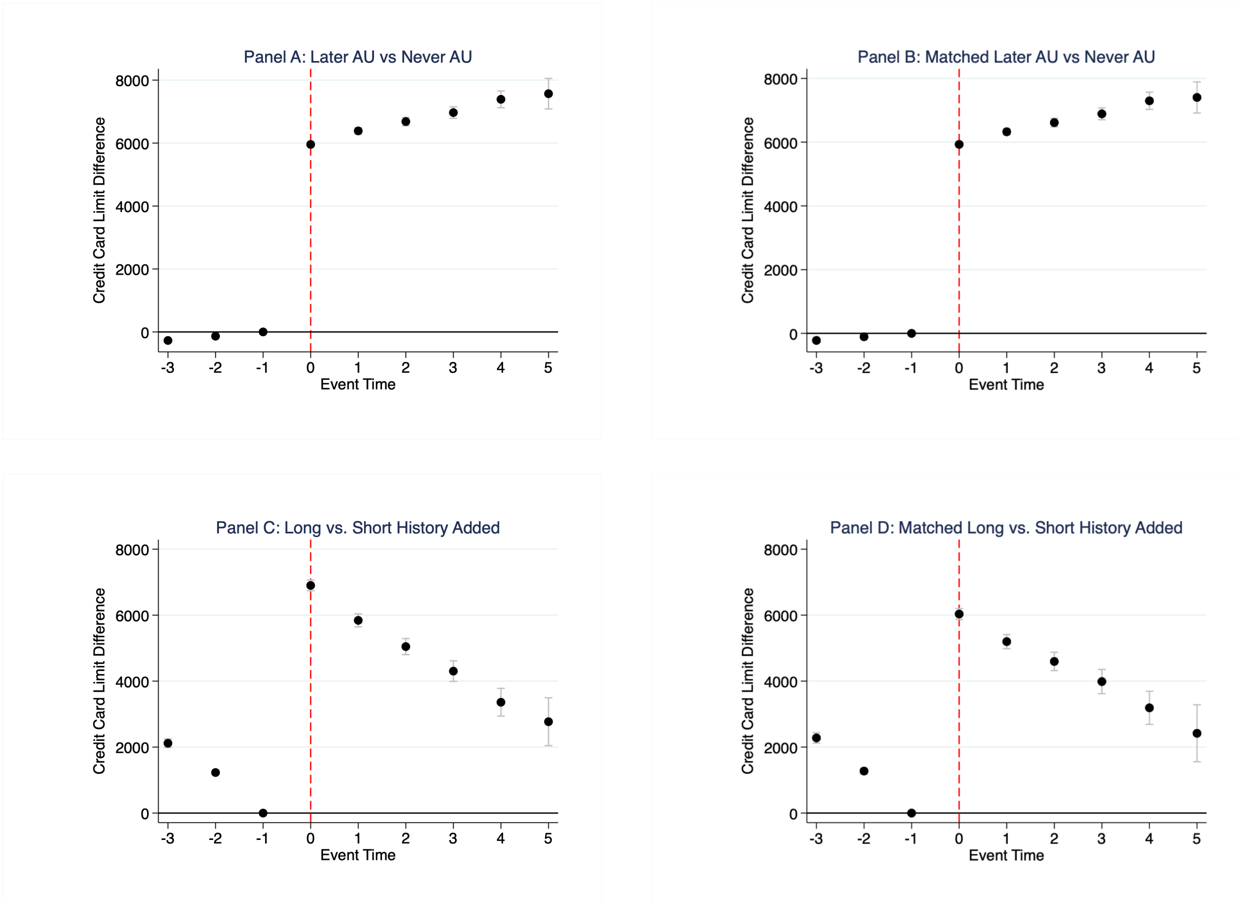

Figure 3: Effect of Authorized User Addition on Credit Card Limits

This figure plots the coefficients from a difference-in-differences specification examining the impact of authorized user account addition on credit card limits. In Panels A and B, the control group is individuals who never received AU status. In Panels C and D, the control group is individuals who were added as AUs but did not experience an increase in the length of their credit histories as a result. We plot coefficients from three years prior to AU addition to five years after. The specification uses the Callaway and Sant'Anna (2021) estimator, including borrower- and ZIP-code-level controls, as well as individual and year fixed effects. Coefficients are plotted with 95% confidence intervals, with standard errors clustered at the individual level.

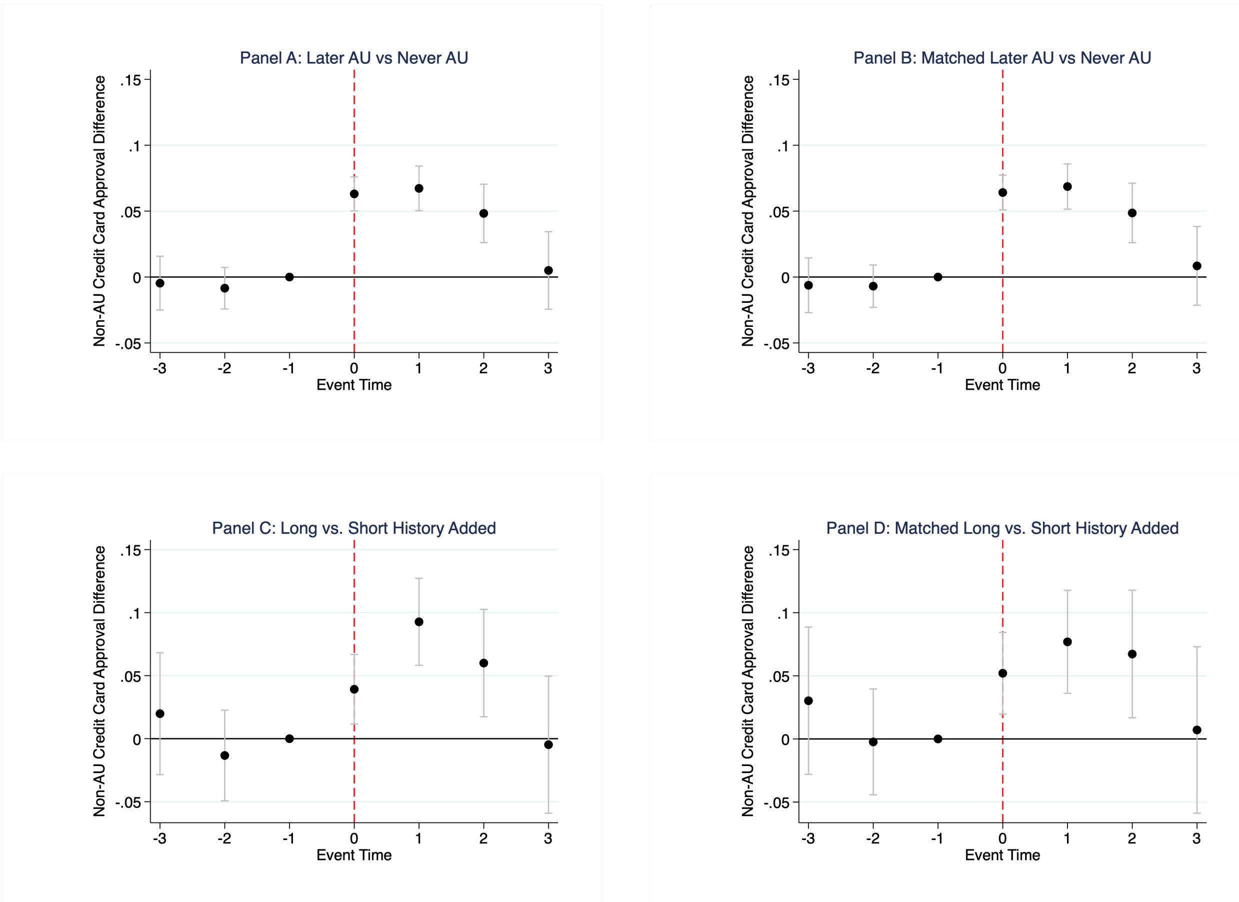

Figure 4: Effect of Authorized User Addition on Non-AU Credit Card Approval

This figure plots the coefficients from a difference-in-differences specification examining the impact of authorized user account addition on non-AU credit card approval. In Panels A and B, the control group is individuals who never received AU status. In Panels C and D, the control group is individuals who were added as AUs but did not experience an increase in the length of their credit histories as a result. We plot coefficients from three years prior to AU addition to five years after. The specification uses the Callaway and Sant'Anna (2021) estimator, including borrower- and ZIP-code-level controls, as well as individual and year fixed effects. Coefficients are plotted with 95% confidence intervals, with standard errors clustered at the individual level.

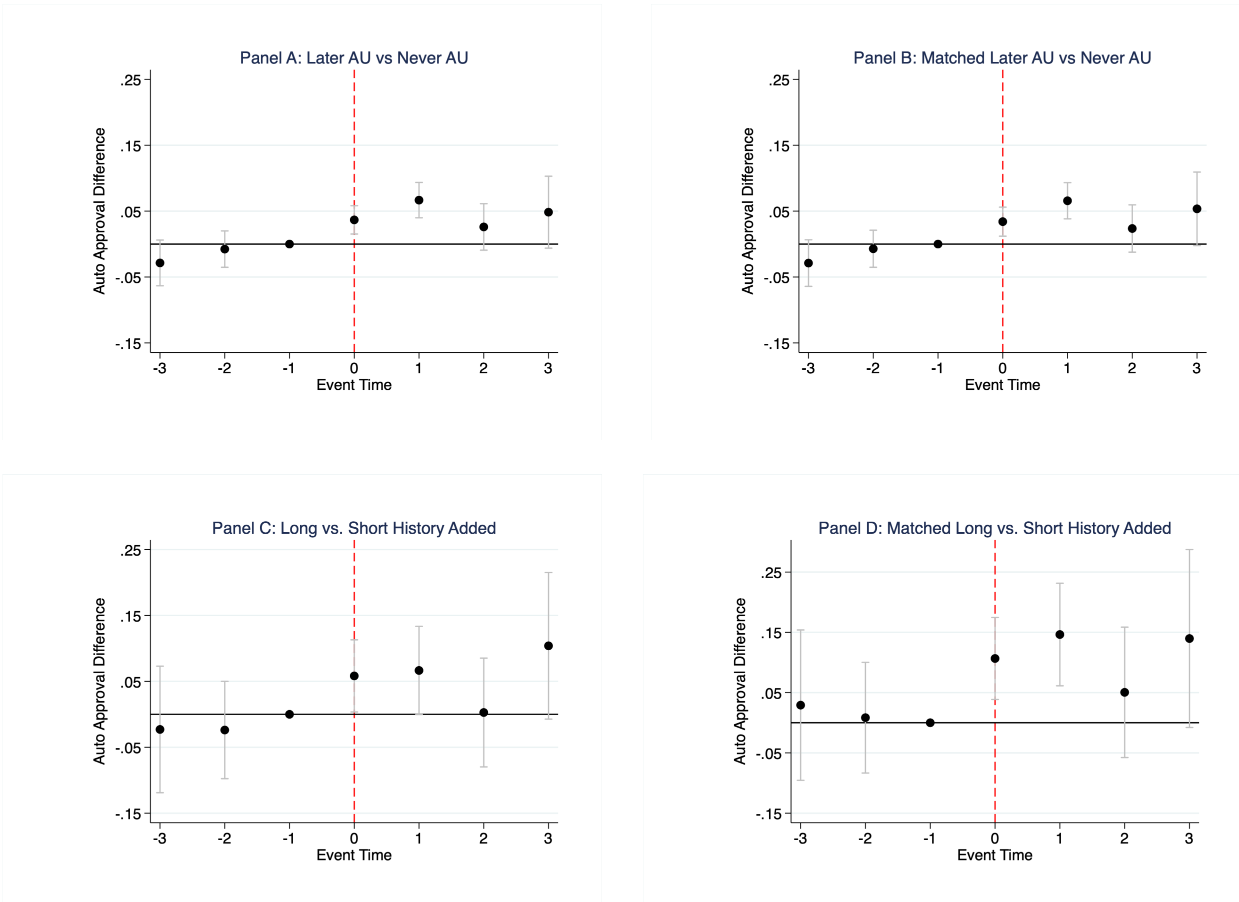

Figure 5: Effect of Authorized User Addition on Access to Auto Loans

This figure plots the coefficients from a difference-in-differences specification examining the impact of authorized user account addition on access to auto loans. In Panels A and B, the control group is individuals who never received AU status. In Panels C and D, the control group is individuals who were added as AUs but did not experience an increase in the length of their credit histories as a result. We plot coefficients from three years prior to AU addition to five years after. The specification uses the Callaway and Sant'Anna (2021) estimator, including borrower- and ZIP-code-level controls, as well as individual and year fixed effects. Coefficients are plotted with 95% confidence intervals, with standard errors clustered at the individual level.

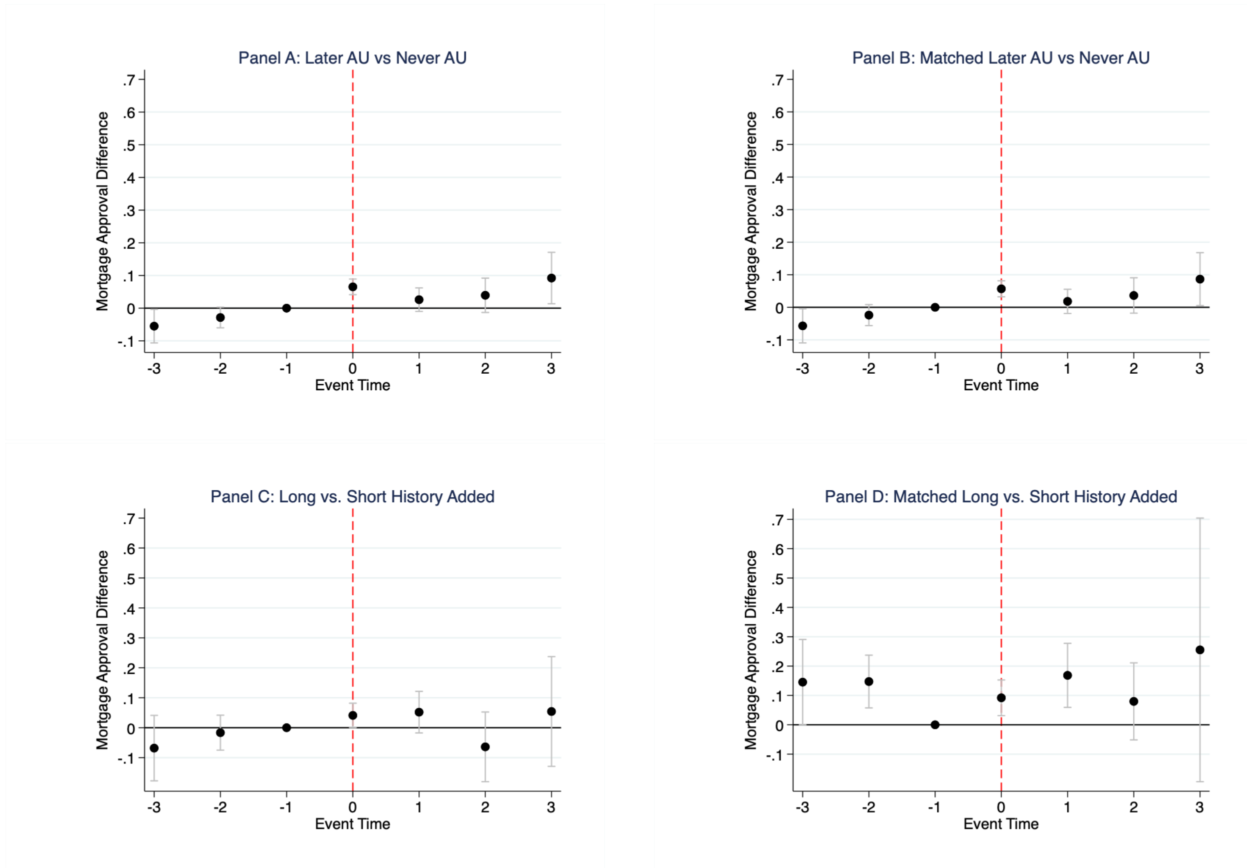

Figure 6: Effect of Authorized User Addition on Access to Mortgages

This figure plots the coefficients from a difference-in-differences specification examining the impact of authorized user account addition on access to mortgages. In Panels A and B, the control group is individuals who never received AU status. In Panels C and D, the control group is individuals who were added as AUs but did not experience an increase in the length of their credit histories as a result. We plot coefficients from three years prior to AU addition to five years after. The specification uses the Callaway and Sant'Anna (2021) estimator, including borrower- and ZIP-code-level controls, as well as individual and year fixed effects. Coefficients are plotted with 95% confidence intervals, with standard errors clustered at the individual level.

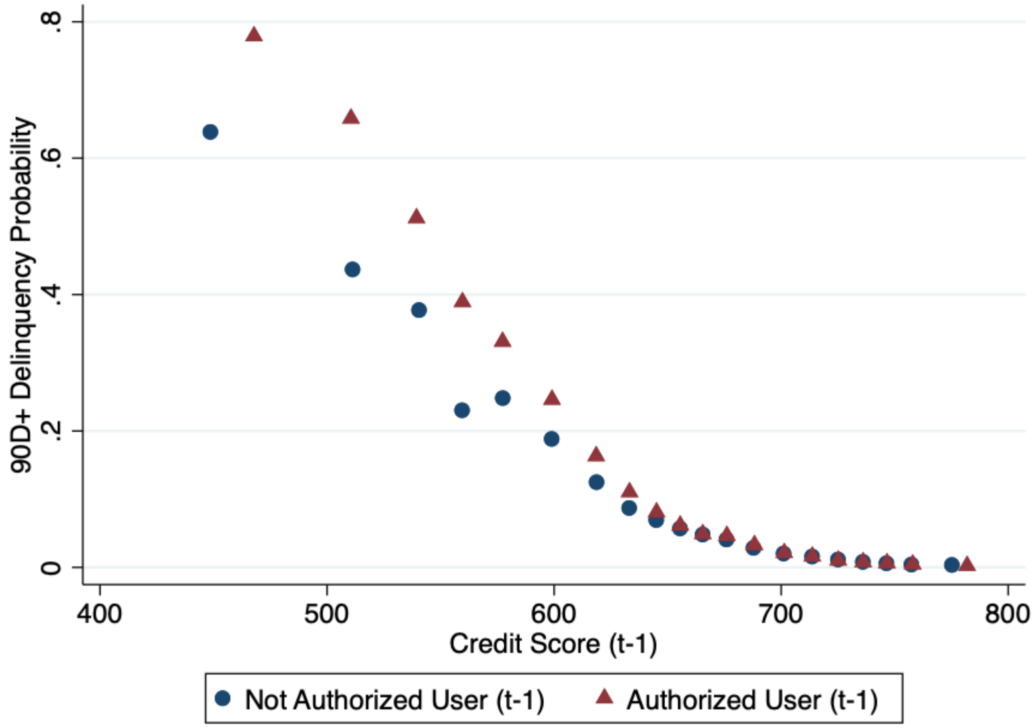

Figure 7: Delinquency Rates by Authorized User Status

This figure plots the average probability of borrowers experiencing a delinquency of 90 days or more within the year, based on credit score at the start of the year. Borrowers with (and without) Authorized User status at the start of the year are grouped into 20-equal sized bins each based on credit scores. In addition to the regular sample restrictions described in Section 3.2, the sample is restricted to individuals with at least one open credit account during the year we measure delinquency.

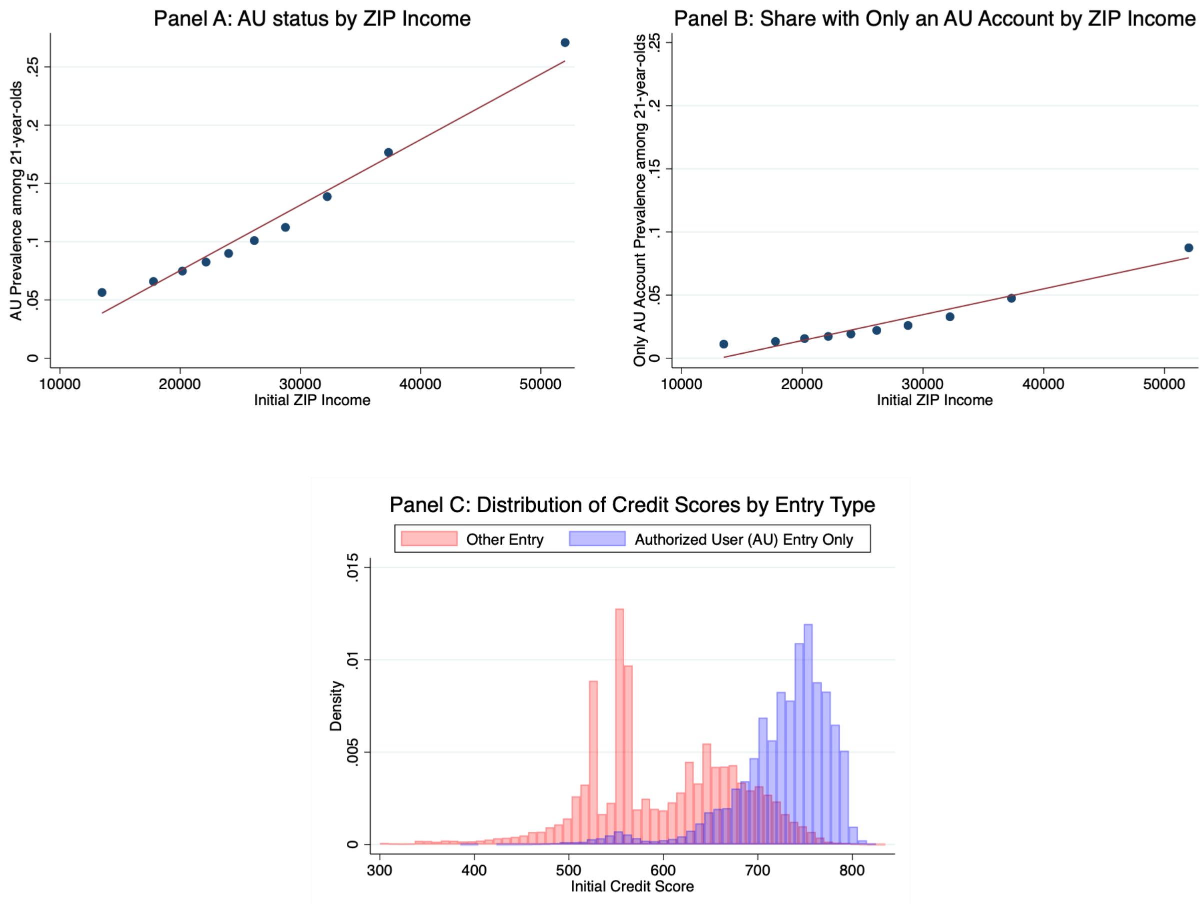

Figure 8: Entry into Credit Bureau Records through Authorized User Accounts

This figure illustrates the prevalence of authorized user (AU) accounts among young adults and the role of AU status in initial entry into the credit bureau records. Panels A and B plot the share of 21-year-olds with an AU account and the share who appear in the credit bureau records *solely* through that account, respectively. The plots show decile bin averages formed based on the ZIP code income measured in the individual's first year of appearance in the data, along with the best fit line. Panel C reports the credit scores at the end of the first year for individuals who enter the credit bureau records through an AU account versus those who enter through other means.

Table 1: Summary Statistics

This table provides summary statistics of the credit bureau data at the individual-year level from 2004 to 2020. In Panel A, the sample includes individuals who are ages 18 to 25 (see Section 3.2 for sample construction details). The six columns present the mean, standard deviation (SD), 10th percentile (P10), 50th percentile (P50), 90th percentile (P90), and the sample size (N). In Panel B, the sample is further restricted to individuals in the first year they appear in the credit bureau data. The first three columns report the mean for the sample of individuals who are added as authorized users, the mean for the sample of individuals who are never authorized users, and the normalized difference between these groups, respectively. The last three columns report the matched sample version (see Section 3.3 for matching procedure details). In Panel C, the sample is restricted to individuals who are added as authorized users. Long History individuals are those who experienced an increase in the length of their credit histories as a result of the authorized user account addition. Short History individuals' credit history length is unaffected by authorized user account addition. The first three columns report the mean for the sample of Long History individuals, the mean for the sample of Short History individuals, and the normalized difference between these groups, respectively. The last three columns report the matched sample version, focusing on the year prior to AU account addition. All variables are defined in Appendix Table A.1.

Panel A: Full Sample	Mean	SD	P10	P50	P90	N
Dependent Variables						
Credit Score$_{i,t}$	609.39	93.68	494.00	616.00	735.00	3,565,791
Credit Limit$_{i,t}$	2,225.91	5,065.92	0.00	0.00	6,993.75	3,565,791
Non-AU Credit Card Approval$_{i,t}$	0.43	0.49	0.00	0.00	1.00	1,053,167
Auto Approval$_{i,t}$	0.63	0.48	0.00	1.00	1.00	628,840
Mortgage Approval$_{i,t}$	0.19	0.39	0.00	0.00	1.00	285,704
90D+ Delinquency$_{i,t}$	0.15	0.36	0.00	0.00	1.00	3,565,791
Credit Score Decline$_{i,t}$	0.37	0.48	0.00	0.00	1.00	2,767,396
Credit Score Change$_{i,t}$	5.35	59.74	-66.00	7.00	73.00	2,767,396
Borrower Characteristics						
Authorized User Status$_{i,t}$	0.04	0.20	0.00	0.00	0.00	3,565,791
Additional History$_{i}$ (months)	32.25	69.85	0.00	0.00	119.00	345,937
Borrower Age$_{i,t}$	22.23	2.05	19.00	22.00	25.00	3,565,791
Thin File$_{i,t}$	0.45	0.50	0.00	0.00	1.00	3,565,791
Young$_{i,t}$	0.37	0.48	0.00	0.00	1.00	3,565,791
Debt-to-Income Ratio$_{i,t}$	0.28	0.60	0.00	0.02	0.76	3,565,791
Debt$_{i,t}$	11,560.23	29,424.25	0.00	594.93	27,745.46	3,565,791
Utilization$_{i,t}$	0.42	0.42	0.00	0.30	0.99	3,565,791
ZIP Controls						
ZIP Income$_{z,t}$	26,991.08	10,953.85	16,168.00	24,727.00	40,119.00	3,565,791
ZIP Fraction Minority$_{z,t}$	0.38	0.28	0.06	0.31	0.85	3,565,791
ZIP Fraction College$_{z,t}$	0.27	0.16	0.11	0.23	0.50	3,565,791

Panel B: Control Group Splits

	Later AU vs Never AU			Matched Later AU vs Never AU		
	Mean (Later Treated)	Mean (Never AU)	Norm. Diff (Later vs Never)	Mean (Later Treated)	Mean (Never AU)	Norm. Diff (Later vs Never)
Dependent Variables						
Credit Score$_{i,t}$	614.56	597.26	0.16	613.21	612.96	0.00
Credit Card Limit$_{i,t}$	1,197.70	947.80	0.05	1,072.52	910.95	0.04
Non-AU Credit Card Approval$_{i,t}$	.	.	.	.	.	.
Auto Approval$_{i,t}$	0.71	0.68	0.05	0.67	0.70	-0.05
Mortgage Approval$_{i,t}$	0.19	0.16	0.06	0.10	0.14	-0.08
90D+ Delinquency$_{i,t}$	0.04	0.08	-0.11	0.04	0.03	0.01
Credit Score Decline$_{i,t}$	.	.	.	.	.	.
Credit Score Change$_{i,t}$	.	.	.	.	.	.
Borrower Characteristics						
Authorized User Status$_{i,t}$	.	.	.	.	.	.
Additional History$_i$ (months)	31.27	.	.	30.94	.	.
Borrower Age$_{i,t}$	19.74	20.72	-0.36	19.69	19.69	0.00
Thin File$_{i,t}$	.	.	.	.	.	.
Young$_{i,t}$	0.83	0.66	0.28	0.84	0.84	0.00
Debt-to-Income Ratio$_{i,t}$	0.15	0.14	0.01	0.10	0.11	0.00
Debt$_{i,t}$	5,441.11	5,069.67	0.01	3,632.42	3,603.10	0.00
Utilization$_{i,t}$	0.34	0.34	-0.01	0.31	0.31	0.01
ZIP Controls						
ZIP Income $_{z,t}$	29,095.23	26,484.19	0.16	28,284.21	28,229.26	0.00
ZIP Fraction Minority$_{z,t}$	0.34	0.39	-0.12	0.35	0.35	-0.01
ZIP Fraction College$_{z,t}$	0.30	0.27	0.16	0.29	0.29	0.00

Panel C: Control Group Splits

	Long vs. Short History Added			Matched Long vs. Short History Added		
	Mean (Long History)	Mean (Short History)	Norm. Diff (Long vs Short)	Mean (Long History)	Mean (Short History)	Norm. Diff (Long vs Short)
Dependent Variables						
Credit Score$_{i,t}$	616.28	613.55	0.03	633.36	632.81	0.01
Credit Card Limit$_{i,t}$	1,157.02	1,221.52	-0.01	1,663.87	1,846.44	-0.03
Non-AU Credit Card Approval$_{i,t}$	.	.	.	.	.	.
Auto Approval$_{i,t}$	0.72	0.71	0.01	0.47	0.46	0.02
Mortgage Approval$_{i,t}$	0.17	0.20	-0.06	0.62	0.56	0.08
90D+ Delinquency$_{i,t}$	0.02	0.05	-0.12	0.09	0.06	0.08
Credit Score Decline$_{i,t}$	.	.	.	.	.	.
Credit Score Change$_{i,t}$	.	.	.	.	.	.
Borrower Characteristics				.	.	.
Authorized User Status$_{i,t}$	.	.	.	.	.	.
Additional History$_{i}$ (months)	86.18	.	.	84.35	0.00	0.94
Borrower Age$_{i,t}$	19.63	19.80	-0.07	21.01	21.01	0.00
Thin File$_{i,t}$	.	.	.	.	.	.
Young$_{i,t}$	0.85	0.82	0.06	0.59	0.59	0.00
Debt-to-Income Ratio$_{i,t}$	0.10	0.18	-0.14	0.13	0.14	-0.03
Debt$_{i,t}$	3,370.78	6,618.98	-0.12	4,646.51	5,067.21	-0.02
Utilization$_{i,t}$	0.25	0.38	-0.23	0.29	0.35	-0.11
ZIP Controls						
ZIP Income $_{z,t}$	31,082.88	27,970.10	0.18	28,935.63	28,789.20	0.01
ZIP Fraction Minority$_{z,t}$	0.33	0.35	-0.05	0.34	0.34	-0.01
ZIP Fraction College$_{z,t}$	0.33	0.29	0.18	0.31	0.30	0.02

Table 2: Effect of Authorized User Addition on Credit Scores

This table examines the average effect of an authorized user acount addition on credit scores. The dependent variable is the individual's credit score. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). *AU Treated*$_i$ is an indicator for whether an individual is added as an authorized user on a credit account after at least one observable year in the data. In Columns 1 and 2, *Post*$_{i,t}$ is an indicator for the time period after the individual initially becomes an authorized user. The control group is individuals who never became authorized users by age 25. Within the set of authorized users, Long *History Treated*$_i$ is an indicator for whether an individual sees an increase in the length of their credit history as a result of the authorized user account addition. In Columns 3 and 4, *Post*$_{i,t}$ is an indicator variable for the time period after the individual initially becomes an authorized user and received an increase in the length of their credit histories as a result. The control group is individuals whose credit history length is unaffected by authorized user addition. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Credit Score			
	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	30.796***	30.177***		
	(0.328)	(0.327)		
Long History Treated$_i$ X Post$_{i,t}$			41.656***	21.847***
			(0.631)	(0.785)
Debt-to-Income Ratio$_{i,t-1}$	-3.640***	-2.777***	-3.000***	-1.296***
	(0.120)	(0.142)	(0.278)	(0.464)
Log Length of Non-AU Credit History$_{i,t-1}$	3.699***	3.464***	6.784***	3.158***
	(0.079)	(0.116)	(0.342)	(0.449)
Severe Delinquency$_{i,t-1}$	-14.670***	-19.176***	-18.442***	-16.811***
	(0.151)	(0.194)	(0.579)	(0.866)
Utilization$_{i,t-1}$	-16.243***	-19.713***	-10.711***	-15.713***
	(0.205)	(0.252)	(0.626)	(0.863)
Log Debt$_{i,t-1}$	0.929***	1.096***	0.030	0.593***
	(0.024)	(0.028)	(0.069)	(0.095)
Log ZIP Income$_{z,t-1}$	1.122***	4.709***	0.153	2.268*
	(0.295)	(0.372)	(0.780)	(1.212)
ZIP Fraction Minority$_{z,t-1}$	2.483***	2.606***	2.693**	3.013*
	(0.425)	(0.523)	(1.275)	(1.772)
ZIP Fraction College$_{z,t-1}$	2.361***	3.762***	0.773	-0.796
	(0.691)	(0.848)	(1.842)	(2.655)
Observations	2,657,285	2,457,046	282,830	198,729
R-squared	0.814	0.801	0.763	0.825
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	609.4	611.2	651.4	653.3

Table 3: Heterogeneity in the Effect of Authorized User Addition on Credit Scores

This table examines the heterogeneous effect of being added as an authorized user on a credit account on credit scores. The dependent variable is the individual's credit score. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). *AU Treated$_i$* is an indicator for whether an individual is added as an authorized user on a credit account after at least one observable year in the data. In Columns 1 and 2, *Post$_{i,t}$* is an indicator for the time period after the individual initially becomes an authorized user. The control group is individuals who never became authorized users by age 25. Within the set of authorized users, Long *History Treated$_i$* is an indicator for whether an individual sees an increase in the length of their credit history as a result of the authorized user account addition. In Columns 3 and 4, *Post$_{i,t}$* is an indicator variable for the time period after the individual initially becomes an authorized user and received an increase in the length of their credit histories as a result. The control group is individuals whose credit history length is unaffected by authorized user addition. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Credit Score			
Panel A: Thin File	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	15.456***	16.734***		
	(0.401)	(0.412)		
AU Treated$_i$ X Post$_{i,t}$ X Thin File$_{i,t}$	33.435***	30.895***		
	(0.526)	(0.536)		
Long History Treated$_i$ X Post$_{i,t}$			17.612***	9.138***
			(0.881)	(1.107)
Long History Treated$_i$ X Post$_{i,t}$ X Thin File$_{i,t}$			44.796***	23.053***
			(1.021)	(1.216)
Observations	2,657,285	2,457,046	282,830	198,729
R-squared	0.814	0.802	0.767	0.826
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	609.4	611.2	651.4	653.3

Dependent Variable:	Credit Score			
Panel B: Young	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	25.097***	24.621***		
	(0.364)	(0.370)		
AU Treated$_i$ X Post$_{i,t}$ X Young$_{i,t}$	21.488***	22.108***		
	(0.546)	(0.568)		
Long History Treated$_i$ X Post$_{i,t}$			39.355***	22.103***
			(0.745)	(0.882)
Long History Treated$_i$ X Post$_{i,t}$ X Young$_{,t}$			24.592***	9.810***
			(0.913)	(1.293)
Observations	2,657,285	2,457,046	282,830	198,729
R-squared	0.814	0.801	0.766	0.825
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	609.4	611.2	651.4	653.3

Table 4: Effect of Authorized User Addition on Credit Card Limits

This table examines the average effect of an authorized user account addition on credit card credit limits. The dependent variable is the person's total credit limit across all cards. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). *AU Treated$_i$* is an indicator for whether an individual is added as an authorized user on a credit account after at least one observable year in the data. In Columns 1 and 2, *Post$_{i,t}$* is an indicator for the time period after the individual initially becomes an authorized user. The control group is individuals who never became authorized users by age 25. Within the set of authorized users, Long *History Treated$_i$* is an indicator for whether an individual sees an increase in the length of their credit history as a result of the authorized user account addition. In Columns 3 and 4, *Post$_{i,t}$* is an indicator variable for the time period after the individual initially becomes an authorized user and received an increase in the length of their credit histories as a result. The control group is individuals whose credit history length is unaffected by authorized user addition. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Credit Card Limits			
	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	6,208.31***	6,031.40***		
	(40.785)	(40.846)		
Long History Treated$_i$ X Post$_{i,t}$			6,104.22***	1,707.20***
			(84.721)	(99.441)
Observations	2,657,285	2,457,046	282,830	198,729
R-squared	0.786	0.790	0.746	0.824
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	2,226	2,256	6,191	5,939

Table 5: Effect of Authorized User Addition on Non-AU Credit Card Approval

This table examines the average effect of an authorized user account addition on credit card approval rates. The dependent variable is an indicator for approval on non-authorized user credit cards, and the sample is restricted to person-years where the person applied for a credit card. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). *AU Treated$_i$* is an indicator for whether an individual is added as an authorized user on a credit account after at least one observable year in the data. In Columns 1 and 2, *Post$_{i,t}$* is an indicator for the time period after the individual initially becomes an authorized user. The control group is individuals who never became authorized users by age 25. Within the set of authorized users, Long *History Treated$_i$* is an indicator for whether an individual sees an increase in the length of their credit history as a result of the authorized user account addition. In Columns 3 and 4, *Post$_{i,t}$* is an indicator variable for the time period after the individual initially becomes an authorized user and received an increase in the length of their credit histories as a result. The control group is individuals whose credit history length is unaffected by authorized user addition. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Non-AU Credit Card Approval			
	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	0.034***	0.041***		
	(0.003)	(0.003)		
AU Treated$_i$	0.032***	0.024***		
	(0.002)	(0.002)		
Long History Treated$_i$ X Post$_{i,t}$			0.067***	0.043***
			(0.006)	(0.009)
Long History Treated$_i$			-0.020***	-0.020***
			(0.005)	(0.008)
Observations	1,041,364	947,872	122,179	76,752
R-squared	0.114	0.170	0.075	0.356
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	0.426	0.431	0.512	0.520

Table 6: Effect of Authorized User Addition on Broader Access to Credit

This table examines the effect of authorized user account addition on broader access to credit beyond credit cards. The dependent variables *Auto Approval* in Panel A and *Mortgage Approval* in Panel B are indicators for the individual successfully obtaining an auto loan, or a mortgage, respectively. The samples are restricted to the person-years in which the person applied for these types of credit. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). *AU Treated$_i$* is an indicator for whether an individual is added as an authorized user on a credit account after at least one observable year in the data. In Columns 1 and 2, *Post$_{i,t}$* is an indicator for the time period after the individual initially becomes an authorized user. The control group is individuals who never became authorized users by age 25. Within the set of authorized users, Long *History Treated$_i$* is an indicator for whether an individual sees an increase in the length of their credit history as a result of the authorized user account addition. In Columns 3 and 4, *Post$_{i,t}$* is an indicator variable for the time period after the individual initially becomes an authorized user and received an increase in the length of their credit histories as a result. The control group is individuals whose credit history length is unaffected by authorized user addition. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Auto Approval			
Panel A: Auto Loans	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	0.027***	0.027***		
	(0.004)	(0.004)		
AU Treated$_i$	0.030***	0.027***		
	(0.003)	(0.004)		
Long History Treated$_i$ X Post$_{i,t}$			0.056***	0.014
			(0.009)	(0.017)
Long History Treated$_i$			-0.026***	-0.003
			(0.009)	(0.015)
Observations	497,236	444,768	55,786	27,396
R-squared	0.143	0.221	0.135	0.498
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	0.626	0.623	0.698	0.685

Dependent Variable:	Mortgage Approval			
Panel B: Mortgages	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	0.029***	0.028***		
	(0.005)	(0.005)		
AU Treated$_i$	0.036***	0.035***		
	(0.004)	(0.004)		
Long History Treated$_i$ X Post$_{i,t}$			0.047***	0.033*
			(0.010)	(0.019)
Long History Treated$_i$			-0.034***	-0.018
			(0.010)	(0.016)
Observations	244,313	214,087	36,931	16,495
R-squared	0.099	0.202	0.106	0.492
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	0.189	0.182	0.255	0.224

Table 7: Delinquency Rates by Authorized User Status

This table examines whether authorized users exhibit a higher probability of serious delinquency (90 days or more) than other borrowers with similar credit scores. The tests in Panel A use the full sample, whereas Panel B focuses on prime borrowers with credit scores of 620 or higher, and Panel C focuses on subprime borrowers with credit scores below 620. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). In addition to the regular sample restrictions, the sample is restricted to individuals with at least one open credit account during the year we measure delinquency. The dependent variable is an indicator for serious delinquency on any form of credit. *Authorized User Status*$_{i,t-1}$ is an indicator variable for whether an individual is an authorized user on a credit account at the start of the year. Within the set of authorized users, *Long History Treated*$_{i,t-1}$ is an indicator variable for an individual being an authorized user on a credit account that led to an increase in the length of their credit history. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The controls include indicators for the individual's 10-point credit score bin at the start of the year, as well as measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Probability of Delinquency			
Panel A: Full Sample	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
Authorized User Status$_{i,t-1}$	0.005***	0.008***		
	(0.001)	(0.001)		
Long History Treated$_{i,t-1}$			0.019***	0.017***
			(0.001)	(0.001)
Observations	1,919,619	1,765,148	253,159	177,341
R-squared	0.380	0.382	0.406	0.400
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Credit Score Bins$_{t-1}$	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	0.132	0.129	0.101	0.0924

Dependent Variable:	Probability of Delinquency			
Panel B: Credit Score$_{t=0}$ ≥620	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
Authorized User Status$_{i,t-1}$	0.004***	0.004***		
	(0.001)	(0.001)		
Long History Treated$_{i,t-1}$			0.013***	0.012***
			(0.002)	(0.002)
Observations	995,465	913,767	129,973	88,934
R-squared	0.355	0.368	0.389	0.386
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Credit Score Bins$_{t-1}$	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	0.0658	0.0692	0.0572	0.0545

Dependent Variable:	Probability of Delinquency			
Panel C: Credit Score$_{t=0}$ <620	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
Authorized User Status$_{i,t-1}$	0.014***	0.015***		
	(0.001)	(0.001)		
Long History Treated$_{i,t-1}$			0.031***	0.026***
			(0.002)	(0.002)
Observations	924,154	851,381	123,186	88,402
R-squared	0.366	0.374	0.407	0.409
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Credit Score Bins$_{t-1}$	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	0.212	0.200	0.152	0.135

Table 8: Do Authorized Users' Credit Scores Decline (Revert) in the Future?

This table examines whether individuals who are added as authorized users ultimately maintain their higher credit scores, or whether their scores subsequently decline/revert toward lower levels. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). In Panel A, the dependent variable is *Credit Score Drop*, an indicator for whether the individual's credit score decreased relative to the prior year. In Panel B, the dependent variable is *Credit Score Change*, which is the change in credit score relative to the prior year. *Authorized User Status*$_{i,t-1}$ is an indicator variable for whether an individual is an authorized user on a credit account at the start of the year. Within the set of authorized users, *Long History Treated*$_{i,t-1}$ is an indicator variable for an individual being an authorized user on a credit account that led to an increase in the length of their credit history. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Credit Score Decline			
Panel A: Probability of Drop	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
Authorized User Status$_{i,t-1}$	0.077***	0.074***		
	(0.003)	(0.003)		
Long History Treated$_{i,t-1}$			0.121***	0.063***
			(0.005)	(0.007)
Observations	2,596,448	2,397,214	221,993	155,013
R-squared	0.249	0.263	0.253	0.392
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	0.367	0.369	0.365	0.359

Dependent Variable:	Credit Score Change			
Panel B: Level Change	Later AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
Authorized User Status$_{i,t-1}$	-5.827***	-6.280***		
	(0.309)	(0.310)		
Long History Treated$_{i,t-1}$			-11.556***	-4.606***
			(0.564)	(0.736)
Observations	2,596,448	2,397,214	221,993	155,013
R-squared	0.242	0.270	0.254	0.401
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	No	Yes	No	Yes
Mean of dependent variable	5.349	4.955	12.08	13.11

Internet Appendix

Table A.1: Variable Definitions

Variable	Definition
Dependent Variables	
Credit Score$_{i,t}$	The person's credit score using the VantageScore
Credit Limit$_{i,t}$	Total credit limit on open credit cards (in 2015 dollars)
Non-AU Credit Card Approval$_{i,t}$	Indicator for whether the number of non-authorized user sponsored credit cards increase relative to the prior year (defined for years in which they search)
Auto Approval$_{i,t}$	Indicator for the person successfully obtaining an auto loan (defined for years in which they search)
Mortgage Approval$_{i,t}$	Indicator for the person successfully obtaining a mortgage (defined for years in which they search)
Severe Delinquency$_{i,t}$	Indicator for serious delinquency (90 days or more) on any form of credit
Credit Score Decline$_{i,t}$	Indicator for the person's credit score decreasing relative to the prior year
Credit Score Change$_{i,t}$	Change in the person's credit score relative to the prior year
Number of Open Accounts$_{i,t}$	Number of open credit accounts across all types
Borrower Characteristics	
AU Treated$_{i}$	Indicator for the person being someone who gains authorized user status after entering the data
Post$_{i,t}$	Indicator for the person in the AU Treated group having gained authorized user status
Authorized User Status$_{i,t}$	Indicator for the person having authorized user status on a credit account during the current year
Long History Treated$_{i}$	Indicator for the person whose credit history increases when they gain authorized user status. Within the set of authorized users, the control group consists of individuals whose credit history length is unaffected by authorized user addition.
Log Length of Non-AU Credit History$_{i,t-1}$	Log of the number of months since oldest non-AU account was opened
Borrower Age$_{i,t}$	Person's current age
Thin File$_{i,t}$	Indicator for the person having less than or equal to one open credit account at the start of the year
Young$_{i,t}$	Indicator for the person being 21 years old or younger
Debt-to-Income Ratio$_{i,t-1}$	Person's total debt-to-income ratio at the start of the year, excluding authorized user accounts
Debt$_{i,t-1}$	Person's total debt at the start of the year, excluding authorized user accounts (in 2015 dollars)
Utilization$_{i,t-1}$	Utilization rate on all non-AU accounts
ZIP Controls	
ZIP Income $_{z,t-1}$	ZIP code level per-capita income from the American Community Survey (ACS)
ZIP Fraction Minority$_{z,t-1}$	ZIP code level minority population share from the ACS
ZIP Fraction College$_{z,t-1}$	ZIP code level fraction of people 25 years or older with a college degree based on the ACS

Table A.2: Summary Statistics for the Always AU Group

This table provides summary statistics of the credit bureau data at the individual-year level from 2004 to 2020. The sample includes individuals who are ages 18 to 25 (see Section 3.2 for sample construction details). For this analysis, we include individuals who entered the data as authorized users (i.e., the Always AU group). The sample is restricted to the first year that individuals appear in the credit bureau data. The three columns present the mean for the Always AU group, the mean for all other individuals, and the normalized difference between these groups, respectively. All variables are defined in Appendix Table A.1.

	Always AU vs All Others		
	Mean (Always AU)	Mean (All Others)	Norm. Diff (Always vs Others)
Dependent Variables			
Credit Score$_{i,t}$	713.18	598.58	1.13
Credit Card Limit$_{i,t}$	12,937.13	993.93	0.91
Non-AU Credit Card Approval$_{i,t}$	.	.	.
Auto Approval$_{i,t}$	0.72	0.68	0.07
Mortgage Approval$_{i,t}$	0.30	0.17	0.23
90D+ Delinquency$_{i,t}$	0.02	0.07	-0.16
Credit Score Decline$_{i,t}$	.	.	.
Credit Score Change$_{i,t}$	.	.	.
Borrower Characteristics			
Authorized User Status$_{i,t}$	.	.	.
Additional History$_{i}$ (months)	71.77	31.27	0.36
Borrower Age$_{i,t}$	20.58	20.65	-0.02
Thin File$_{i,t}$	.	.	.
Young$_{i,t}$	0.67	0.67	-0.01
Debt-to-Income Ratio$_{i,t}$	0.16	0.14	0.03
Debt$_{i,t}$	9,202.00	5,129.29	0.11
Utilization$_{i,t}$	0.24	0.34	-0.18
ZIP Controls			
ZIP Income $_{z,t}$	33,133.97	26,682.93	0.34
ZIP Fraction Minority$_{z,t}$	0.34	0.39	-0.11
ZIP Fraction College$_{z,t}$	0.35	0.27	0.34

Table A.3: Effect on Credit Scores and Credit Access: Alternate Treatment Definition

This table examines the effect of authorized user account addition on credit scores and credit access, using the alternate treatment definition based on an individual's current authorized user status. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). The dependent variable in Column 1 is an individual's current credit score. The dependent variables in Columns 2-4 are *Non-AU Credit Card Approval*, *Auto Approval*, and *Mortgage Approval*, which are indicators for the individual successfully obtaining a non-authorized user sponsored credit card, an auto loan, or a mortgage, respectively. *Authorized User Status*$_{i,t}$ is an indicator variable for whether an individual is an authorized user during the year. The control group is individuals who never became authorized users by age 25. The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Dependent Variable:	Credit Score (1)	Non-AU Credit Card Approval (2)	Auto Approval (3)	Mortgage Approval (4)
AU Treated$_i$ X Post$_{i,t}$	32.36***	0.05***	0.05***	0.05***
	(0.291)	(0.003)	(0.004)	(0.004)
Observations	2,657,285	1,041,364	497,236	244,313
R-squared	0.814	0.114	0.143	0.099
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Cohort-Year FE	609.4	0.426	0.626	0.189
Mean of dependent variable	5.349	5.362	12.08	12.64

Table A.4: Effect on Credit Scores and Credit Access: Excluding Married Individuals

This table examines the effect of authorized user account addition on credit scores and credit access, excluding married individuals. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). Individuals' marriage status is not included in credit reports. However, starting in 2010, the credit bureau began estimating an individuals' marriage status based on a predictive model. As a result, we further restrict this sample to individuals who are between 18 and 25 years old in or after 2010, when the marriage status flag was made available by the credit bureau. The dependent variable in Column 1 is an individual's current credit score. The dependent variables in Columns 2-4 are *Non-AU Credit Card Approval*, *Auto Approval*, and *Mortgage Approval*, which are indicators for the individual successfully obtaining a non-authorized user sponsored credit card, an auto loan, or a mortgage, respectively. *AU Treated*$_i$ is an indicator variable for whether an individual is added as an authorized user on a credit account after at least one observable year in the data. Within the set of authorized users, Long *History Treated*$_i$ is an indicator variable for whether an individual is added as an authorized user on a credit account after at least one observable year in the data and experienced an increase in the length of their credit histories as a result. In Panel A, *Post*$_{i,t}$ is an indicator variable for the time period after the individual initially becomes an authorized user. The control group is individuals who never became authorized users by age 25. In Panel B, *Post*$_{i,t}$ is an indicator variable for the time period after the individual initially becomes an authorized user and received an increase in the length of their credit histories as a result. The control group is individuals whose credit history length is unaffected by authorized user addition. All other interactions are included but not reported. The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Credit Score	Non-AU Credit Card Approval	Auto Approval	Mortgage Approval
Panel A: Later AU vs Never AU	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	33.86***	0.05***	0.03***	0.03***
	(0.548)	(0.005)	(0.007)	(0.008)
Observations	1,060,180	420,922	215,743	80,401
R-squared	0.835	0.108	0.136	0.086
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	613.5	0.453	0.615	0.145

Dependent Variable:	Credit Score	Non-AU Credit Card Approval	Auto Approval	Mortgage Approval
Panel B: Long vs. Short History Added	(1)	(2)	(3)	(4)
Long History Treated$_i$ X Post$_{i,t}$	49.27***	0.08***	0.06***	0.06***
	(1.028)	(0.010)	(0.015)	(0.017)
Observations	110,493	48,646	22,489	11,260
R-squared	0.803	0.078	0.133	0.120
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	657.4	0.527	0.683	0.195

Table A.5: Effect on Credit Scores and Credit Access: Sample Restricted to 2011-2019

This table examines the effect of authorized user account addition on credit scores and credit access. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). We restrict the sample further to observations from 2011 to 2019 to avoid potential confounding effects of the 2008 Financial Crisis or the COVID-19 pandemic. The dependent variable in Column 1 is an individual's current credit score. The dependent variables in Columns 2-4 are *Non-AU Credit Card Approval*, *Auto Approval*, and *Mortgage Approval*, which are indicators for the individual successfully obtaining a non-authorized user sponsored credit card, an auto loan, or a mortgage, respectively. *AU Treated$_i$* is an indicator variable for whether an individual is added as an authorized user on a credit account after at least one observable year in the data. Within the set of authorized users, Long *History Treated$_i$* is an indicator variable for whether an individual is added as an authorized user on a credit account after at least one observable year in the data and experienced an increase in the length of their credit histories as a result. In Panel A, *Post$_{i,t}$* is an indicator variable for the time period after the individual initially becomes an authorized user. The control group is individuals who never became authorized users by age 25. In Panel B, *Post$_{i,t}$* is an indicator variable for the time period after the individual initially becomes an authorized user and received an increase in the length of their credit histories as a result. The control group is individuals whose credit history length is unaffected by authorized user addition. The control variables include measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p <0.10.

Dependent Variable:	Credit Score	Non-AU Credit Card Approval	Auto Approval	Mortgage Approval
Panel A: Later AU vs Never AU	(1)	(2)	(3)	(4)
AU Treated$_i$ X Post$_{i,t}$	33.30***	0.05***	0.04***	0.03***
	(0.463)	(0.004)	(0.005)	(0.006)
Observations	1,432,641	547,175	293,673	114,445
R-squared	0.818	0.099	0.128	0.097
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	612.2	0.460	0.627	0.173

Dependent Variable: Panel B: Long vs. Short History Added	Credit Score (1)	Non-AU Credit Card Approval (2)	Auto Approval (3)	Mortgage Approval (4)
Long History Treated$_i$ X Post$_{i,t}$	49.40***	0.10***	0.07***	0.04***
	(0.900)	(0.008)	(0.012)	(0.015)
Observations	156,074	67,017	32,914	17,263
R-squared	0.781	0.068	0.124	0.111
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
Individual FE	Yes	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	652.6	0.531	0.690	0.233

Table A.6: Delinquency Rates by Authorized User Status, including the Always AU Group

This table examines whether authorized users exhibit a higher probability of serious delinquency (90 days or more) than other borrowers with similar credit scores. The individual-year level data are from a data set of credit bureau records (see Section 3.2 for sample construction details). In addition to the regular sample restrictions, the sample is restricted to individuals with at least one open credit account during the year we measure delinquency. For this analysis, we include individuals who entered the data as authorized users (the Always AU group). The dependent variable is an indicator for serious delinquency on any form of credit. *Authorized User Status*$_{i,t-1}$ is an indicator variable for whether an individual is an authorized user on a credit account at the start of the year. Within the set of authorized users, *Long History Treated*$_{i,t-1}$ is an indicator variable for an individual being an authorized user on a credit account that led to an increase in the length of their credit history. Columns 2 and 4 restrict the sample to matched treatment-control pairs based on pre-treatment credit characteristics (see Section 3.3 for matching procedure details). The controls include indicators for the individual's 10-point credit score bin at the start of the year, as well as measures of credit usage and ZIP code-level demographics. All variables are defined in Appendix Table A.1. Standard errors are clustered by individual. *** p<0.01, ** p<0.05, * p<0.10.

Dependent Variable:	Probability of Delinquency			
	Later or Always AU vs. Never AU		Long vs. Short History Added	
	Full Sample	Matched Sample	Full Sample	Matched Sample
	(1)	(2)	(3)	(4)
Authorized User Status$_{i,t-1}$	0.017***	0.013***		
	(0.000)	(0.001)		
Long History Treated$_{i,t-1}$			0.021***	0.017***
			(0.001)	(0.001)
Observations	2,219,561	2,055,340	552,068	178,496
R-squared	0.386	0.390	0.412	0.400
Borrower and ZIP Controls	Yes	Yes	Yes	Yes
Credit Score Bins$_{t-1}$	Yes	Yes	Yes	Yes
Age Indicators	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Mean of dependent variable	0.120	0.118	0.0726	0.0927