The costs of financial fraud victimization*

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This paper examines the extent of financial fraud victimization, who becomes a victim, and the costs of victimization. Our setting focuses on identity theft, one of the most common types of fraud, comprising over 20% of all reported fraud in the U.S. We find that between 2010 and 2022 credit profiles for over 26 million borrowers included a flag for being an identity theft victim. An average victim reported two fraudulent accounts on which they collectively owed $28,278. Low income, younger borrowers, and those with worse credit histories are more likely to become victims. While an average borrower takes three years to become aware that they have become a victim, over 26% of them find out when they apply for new credit. We find considerable costs associated with victimization as access to credit substantially declines for victims relative to non-victim borrowers following victimization. Victim borrowers are also more likely to file for bankruptcy, be foreclosed upon, and become delinquent post victimization. Not only are low income borrowers more likely to become a victim but conditional on victimization they experience higher costs and decline in access to credit, thereby exacerbating the credit access gap over the income distribution.

Keywords: Financial fraud, fraud, identity theft, victimization, access to credit, financial distress, credit access gap

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1 Introduction

Financial fraud and scams are pervasive affecting millions of individuals every year in the U.S.[1] While some types of fraud incur immediate pecuniary losses, long term costs and implications of fraud victimization remain unclear. On the one hand, if measures in place to protect consumers against fraud losses are effective or victims are high net worth individuals able to absorb short run costs, the long run implications may not be meaningful. On the other hand, if current measures do not offer sufficient protection or victims are not able to absorb temporary losses, long-run costs may be substantial. Which effect dominates is an empirical question the answer to which can help guide interventions.

In this paper, we use detailed micro-data to document the extent of financial fraud victimization, who becomes a victim, and the long-term costs of victimization. We focus on identity theft, one of the most common types of fraud, to answer these questions.[2] Identity theft has increased dramatically over the past couple of decades with the rise of collection and storage of personal information across all forms of commerce and services (Burnes et al. (2020)), and constituted over 20% of fraud reports received by the FTC in 2022 (1.1 million of the 5.2 million reports). This is one of the first papers to shed light on fraud victims and costs associated with victimization.

Our analysis leverages anonymized data on consumer credit histories from Equifax Inc., one of the three major credit bureaus in the U.S. This data covers the entire population of individuals with some form of credit history and has information both at the individual- and credit line-levels. At the individual-level, we observe overall credit accounts and balances along with their performance, demographic information like age and geographic location,

1. The Federal Trade Commission (FTC) received over 5.1 million fraud reports in 2022 alone. More information can be found in the press release from the FTC accessible through this link: https://www.ftc.gov/news-events/news/press-releases/2023/02/new-ftc-data-show-consumers-reported-losing-nearly-88-billion-scams-2022

2. Identity theft constituted over 20% fraud reports received by the FTC in 2022 (1.1 million of the 5.2 million reports).

and information on financial distress events like bankruptcy filings, and foreclosures among others. This also includes a flag for being a victim of identity theft self reported by consumers. At the credit line-level we observe details like account type (e.g., credit card, student loan), account age, total borrowing, account balance, any missed or late payments, and defaults.

We begin by documenting several stylized facts regarding identity theft victimization. First, credit profiles for over 26 million borrowers included a flag for being an identity theft victim between 2010 and 2022 (i.e., 8.7% of 306 million unique borrowers in the U.S.). Second, more than six million borrowers simultaneously disputed at least one fraudulent account when they flagged that they have been victimized. While an average borrower disputed two fraudulent accounts, the average balance a victim owed on these accounts is $28,278. Third, credit cards comprise 50% of all fraudulent accounts with 19.6% and 14.4% being factoring and student loan accounts respectively. Fourth, low income, younger borrowers, and those with worse credit histories are more likely to become victims. Fifth, an average borrower takes 3 years to report victimization (likely because they are unaware of it during this time). Finally, over 26% of reporting borrowers likely discover that they have been victims when they apply for new credit.

Fraudulent accounts on victims' credit profiles resulting from identity theft are usually not accompanied with immediate pecuniary costs. Instead they are likely to affect victims' credit scores, debt-to-income ratios, and eventually access to credit, especially if these accounts enter default (e.g., when fraudsters don't repay and victims are unaware). The extent of these costs depends on two factors. First, how and when do borrowers become aware of victimization. If they discover this while attempting to access credit, they are likely to either be denied or receive more costly credit. Alternatively if they regularly monitor their credit reports and become aware relatively early post victimization, they may be able to resolve discrepancies in their credit reports prior to any credit demand. Second, what happens when the borrowers attempt to recover from theft. While borrowers can report a fraud flag on their credit reports, any changes on the reported accounts need to come from the lenders. Usually lenders conduct their internal investigations when identity theft gets reported and only change their reporting of the accounts if their investigations conclude them to be fraudulent. From the victims' perspective, there is uncertainty regarding both the outcome and duration of such investigations.

In the second part of the paper, we assess these potential costs of victimization by evaluating the association between victimization and access to credit and financial distress. We employ a difference-in-differences approach that captures the relative changes in outcomes around victimization for victims compared to non-victim borrowers. Since there are ex-ante differences across victims and non-victims, we saturate the model with a number of fixed effects to account for these differences. In particular, we include credit score, age, total debt balance, number of delinquencies, and collections all measured one quarter prior to victimization with each of them interacted with time to control for any time varying differences across borrowers different along these dimensions. All specifications include individual fixed effects to control for time invariant differences at the borrower level. The identifying assumption for this approach is that of parallel trends, i.e., controlling for all differences in our specification the residual variation in outcome variables between victim and non-victim borrowers trends parallelly if not for victimization.

We find considerable long term costs associated with fraud victimization. Victim borrowers open lower number of new accounts and balances relative to non-victim borrowers. Total number of new accounts and balances are 100% and 45% lower for victims than non-victims when compared to the unconditional mean. The absence of differential trends between victim and non-victim borrowers provides some assurance that our empirical specification appropriately controls for ex-ante differences between them. These results are likely driven by a decline in access to credit rather than changes to credit demand. While the number of credit applications do not differentially change for victims, their credit scores relatively decline by more than 10 points and remain deflated for over two years following victimization. Similarly, credit denial rates relatively increase by 5.8% when compared to the mean and remain elevated for at least two years. The reduced credit access is accompanied by higher incidences of financial distress including bankruptcy filing, foreclosures, and delinquencies. The likelihood for bankruptcy filing and becoming foreclosed increase by 64% and 8%, relative to the mean, for victims compared to non-victim borrowers. Such financial distress events have long run repercussions as they are included in credit reports for up to 10 years following the event.

Lower access to credit makes households more susceptible to shocks since credit often acts as a buffer tool to absorb negative shocks and smooth consumption. Hence those with lower access are more likely to enter financial distress which further reduces credit access moving forward and creates a vicious cycle. Borrowers with ex-ante lower savings and higher credit constraints are more reliant on credit access to negotiate against shocks. Consistent with this hypothesis, we find our results to be stronger for borrowers with low income and worse credit scores. In combination with the earlier summary facts, our results suggest that not only are low income borrowers more likely to become a victim but conditional on victimization they experience higher costs and decline in access to credit, thereby exacerbating the credit access gap over the income distribution.

Our paper relates to the emerging literature on financial fraud. Our work complements the descriptive analysis conducted by Burnes et al. (2020), who use survey data and document the role of individual-level behaviors, such as online purchasing frequency and data protection policies, and data breaches as determinants of identity theft victimization. In recent work, Bian et al. (2023) document the role of data collection and sharing by companies relating to their consumers in driving financial fraud. The authors find that policies that limit data sharing and tracking significantly reduced financial fraud complaints within more affected geographies. Some studies focus on financial fraud committed against elderly individuals.

Carlin et al. (2020) examine the role of financial institutions and policies to prevent abuse against elderly. They find that deputizing financial professionals across different U.S. states helps prevent financial fraud against elderly.

DeLiema et al. (2020) develop and field a module on investment and prize/lottery fraud in the 2016 Health and Retirement Study, specifically targeting individuals aged 50 and older. Their analysis reveals the incidence of investment and prize/lottery fraud, as well as prospective risk factors associated with these types of financial fraud. Another study by Alves and Wilson (2008) focuses on the disproportionate impact of telemarketing fraud on older adults, particularly those who are socially isolated. Their data was obtained from a questionnaire completed by twenty-eight older adult telemarketing fraud victims, assessing variables related to vulnerability to telemarketing fraud. DeLiema (2018) distinguishes between two forms of financial victimization that target older adults: elder financial exploitation by individuals in positions of trust, and elder fraud by predatory strangers. Their research highlights the different patterns and risk factors associated with these two types of financial fraud. Another study by DeLiema et al. (2012) recruit Spanish-speaking Latino older adults aged 66 and over living in low-income communities in Los Angeles to assess the frequency of various types of abuse and neglect, including financial exploitation. The authors found high rates of victimization among this vulnerable population. James et al. (2014) examine the correlates of susceptibility to scams in a cohort of 639 community-dwelling older adults without dementia. They found that susceptibility was positively associated with age and negatively associated with income, cognition, psychological well-being, social support, and literacy. Lichtenberg et al. (2013) examine the national prevalence of older adults who report having been victims of fraud, created a population-based model for predicting fraud, and investigated how fraud is experienced by the most psychologically vulnerable older adults.

We use micro-data for the entire population of the U.S. and contribute to this literature by examining the prevalence and distribution of identity fraud over the population, and evaluating the financial costs associated with victimization.

Our study also relates to a growing literature that examines the extent of misconduct and fraud within the finance sector (e.g., Dimmock and Gerken, 2012; Griffin and Maturana, 2016; Gurun et al., 2016; Mian and Sufi, 2017; Gurun et al., 2018; Parsons et al., 2018; Dimmock et al., 2021; Tookes and Yimfor, 2021; Celerier and Tak, 2023), and how financial institutions and labor markets discipline finance employees for both poor performance and misconduct/fraud (e.g., Chevalier and Ellison, 1999; Egan et al., 2019; Griffin et al., 2019; Ellul et al., 2020; Gao et al., 2020). While Ellul et al. (2020) document that asset managers working for funds liquidated following persistently poor performance experience demotions and declines in imputed compensation, Gao et al. (2020) show that banks discipline loan officers involved in originating corporate loans that end up performing poorly. Griffin et al. (2019) document that employees involved in residential mortgage-backed security (RMBS) securitization prior to the great recession did not experience differential job retention, promotion, and external job opportunities relative to similar non-RMBS employees. Egan et al. (2019) document the widespread nature of misconduct among financial advisors and that significant fraction of advisors who turnover following a misconduct get rehired within the industry, albeit in less reputable firms that on average pay lower compensation to their employees.

2 Data & Sample

2.1 Data

Our analysis relies on anonymized data on consumer credit histories from Equifax Inc., one of the three major credit bureaus in the U.S. This data covers the entire population of borrowers and has two components with information at the individual- and credit line-levels.

The individual-level data include historical information on overall credit accounts and balances along with their performance, demographic information like age and geographic location, and information on financial distress events like bankruptcy filings, foreclosures, collections, and medical defaults among others. Importantly for us, they include a flag for being a victim of financial fraud self-reported by consumers. Any individual who has been a victim of fraud or identity theft can place this alert/flag on their credit file with the credit bureaus at no cost. Having this flag on the credit file is the first step in repairing any potential damage that the theft might have on consumers' credit scores and profiles. It also ensures that lenders across the country will not approve new credit prior to contacting the consumer or requiring additional identity checks.

The credit bureaus allow consumers to place three types of fraud alerts. First, an initial fraud alert that anyone including those who suspect of being or even becoming a victim can place on their file. This alert creates a flag that stays on the file for one year. Second, an active duty alert that anyone on active military duty can place on their file for one year. Third, an extended fraud alert that requires the consumer to furnish a copy of identity theft report that they've filed with any federal, state, or local enforcement agencies (e.g., federal trade commission report, police report etc.). This fraud alert stays on the file for seven years and excludes borrowers from credit card and insurance offers for five years. The data allows us to observe the type of alert along with the presence of the victim fraud.

The credit line-level data include information at the monthly frequency for all individuals with some form of credit history in the U.S., and include information such as account type (e.g., credit card, student loan), account age, total borrowing, account balance, any missed or late payments, and defaults. We use the credit line-level data to identify the accounts that were reported to be fraudulent. This allows us to track the date of victimization as opening date for these accounts as opposed to the reporting date in individual-level data.

2.2 Sample construction

We begin with all borrowers that had an identity theft flag on their credit report anytime between 2010 and 2022. While the individual-level data allows us to identify borrowers who reported to be victims along with reporting date, we cannot observe the date that a borrower was victimized. The reporting and victimization dates can differ, especially if borrowers do not know that they have been a victim of identity theft immediately. The U.S. government's website recognizes this issue and advises consumers to pay attention to bills for items they did not buy, debt collection calls for accounts they did not open, information on borrowers' credit reports for accounts that they did not open, and denials of loan applications to help become aware of victimization.[3] We overcome this limitation by combining data from both the individual- and credit line-levels.

The credit line-level data includes flags for accounts whose reported information is disputed by the consumer. We merge data on all disputed credit lines to the individual-level data using anonymized borrower identifier and keep those accounts where the disputed flag first appeared at the same time as the fraud flag first appeared at the individual-level reports. We classify these accounts disputed by consumers during the same year-quarter that they report a fraud flag on their credit reports as fraudulent accounts. These accounts were either fraudulently opened or include unauthorized transactions. However, we argue that most of these accounts are likely to be opened fraudulently since unauthorized transactions can be relatively easily reversed by reporting to the lender of the account and hence borrowers do not have incentives to both report an identity theft flag and dispute an account simultaneously with the credit bureaus. We then use the earliest account opening date of the fraudulent accounts at the borrower level as the date of victimization. To the extent that these accounts include those with unauthorized transactions, our estimates are likely to be biased towards zero since no victimization took place at the account opening date of

3. More info can be found using this link: https://www.usa.gov/identity-theft

such accounts.

Our outcome variables for these borrowers come from the individual-level data available from 2010 through 2022. We apply two additional restrictions to the sample. First, we restrict it to borrowers victimized between 2011 and 2021 so we can measure outcome variables for at least one year prior to first victimization and following last victimization. Second, we confine to accounts that are not more than 10 years old at the time the dispute was reported.[4] This gives us our final sample of 3 million borrowers associated with 6.3 fraudulent accounts. While we use this sample for our analysis on costs associated with victimization, the other intermediate samples help document stylized facts related to identity theft in general.

3 Stylized facts

Since little is known about identity theft victimization, we begin our analysis by documenting several stylized facts based on our data. First, credit reports for over 26 million borrowers included a fraud flag between 2010 and 2022. This shows that identity theft remains pervasive as it affects 8.7% of 306 million unique borrowers or about 10% of the total adult population in the U.S.[5] over this period. The ubiquitous nature of these thefts further underscores the importance of understanding the costs associated with them. Of these, 24.2 and 3.9 million reports include 1 and 7 year flags respectively. Since some reports include both flags at different points in time, the sum adds up to greater than the total number of borrowers. Figure 1 plots the number of reports with fraud flags across years, and shows that it has grown over time stabilizing 2019 onwards.

Second, among borrowers victimized between 2011 and 2021 more than six million dis-

4. While this is an arbitrary cut-off, our results are not sensitive to this assumption.

5. According to the U.S. Census survey of 2020, the adult population defined as 18 years or older was 258.3 million in 2020. More information can be found using this link: https://www.census.gov/library/stories/2021/08/united-states-adult-population-grew-faster-than-nations-total-population-from-2010-to-2020.html#: :text=In%202020%2C%20the%20U.S.%20Census,from%20234.6%20million%20in%202010.

puted at least one fraudulent account simultaneously when they reported being a victim. While an average borrower reported two fraudulent accounts, the average balance a victim owed on these accounts is $28,278. Third, most of these accounts include unsecured debt with 50% of them being credit cards. Figure 2 plots the distribution of the type of accounts classified as fraudulent. Factoring accounts and student loans comprise the two largest categories outside credit cards contributing 19.6% and 14.4% of all accounts respectively.[6] Factoring related identity fraud occurs when false accounts receivables are sold to factoring companies in the name of identity theft victims making them liable for these receipts. Theft related to student loans usually involves thieves enrolling in universities under the victim's name and borrowing on student debt under the pretence to fund both tuition and living expenses.

To shed light on what type of borrowers are more likely to become victims of identity theft, we compare victims to non-victim borrowers on a number of observable characteristics. Figure 3 shows density plots for different characteristics across three sub-groups: victims with 1 year fraud flag on their credit file, those with 7 year fraud flag, and non-victim borrowers. To avoid the influence of victimization on these variables, they are plotted using data prior to victimization for the victim borrowers. Data from the entire panel is used for non-victim borrowers. The plots show that while there are significant differences between victims and non-victims across several of these variables, the differences between borrowers with 1 year versus 7 year fraud flags on their credit reports are not economically meaningful.

The first two panels show that younger borrowers and those with low credit scores are more likely to become victims. While an average victim with a 7 year fraud flag is 37 years old and has an ex-ante credit score of 573, an average non-victim is 45 years old and has a credit score of 676. Panel (c) compares these individuals on income and shows that victim borrowers have lower income than non-victims. Victims with a 7 year fraud flag earn around

6. Factoring is a financial transaction in which a company sells its accounts receivable to a financing company that specializes in buying receivables at a discount. A factoring account usually gets reported to consumer credit reports only after it enters default and gets sold to debt collection companies.

$45k per year compared to non-victims who on average earn over $62k. Victims have higher ex-ante total debt balance than non-victims. As reported in panel (d), victims with a 7 year fraud flag have over $4k higher debt balance than non-victims. Panels (e) through (h) show that this difference is large driven by mortgage and student loan balances. While auto loan balances are not statistically different across victims and non-victims, credit card balances are higher for non-victims. Victim borrowers have higher delinquency and collection accounts on their credit files relative to non-victim borrowers. For example, panel (i) shows that an average borrower with a 7 year fraud flag on the report has 1.44 default accounts relative to only 0.34 for an average non-victim borrower.

We next turn our attention to how long does it take for borrowers to report victimization and how do they discover that they have become victims. An average borrower reports victimization three years after the victimization date. This is likely because they are unaware that they have been victims during this time. Along with not including a fraud flag, the credit reports for these borrowers also do no include any credit freezes between victimization and reporting dates, which further supports the hypothesis that they are unaware of victimization during this time. Over 26% of borrowers that report being victims do so in the quarter during which they apply for the credit for the first time post victimization. This is consistent with the hypothesis that these borrowers become aware of the victimization when they apply for credit. They are likely to either be denied credit or receive more expensive credit. We evaluate this plausibility in the next section.

4 Costs of victimization

4.1 Potential costs

To evaluate the potential costs of identity fraud victimization, we study the association between victimization and individual outcomes. We broadly examine variables that measure two types of costs — access to credit and financial distress. Identity theft and the accompanied fraudulent accounts on the victims' credit profiles are usually not accompanied with any immediate pecuniary costs. Instead they are likely to affect access to credit through their effect on victims' credit scores and debt-to-income (DTI) ratios. Higher balances on credit files will mechanically lead to higher DTI ratios which negatively affects credit scores. The impact on credit score is magnified when fraudulent accounts, unknown to the victim, become delinquent. Lower access to credit can in-turn make households more susceptible to shocks since credit often acts as a buffer tool to absorb negative shocks. Hence those with lower credit access are potentially more likely to experience financial distress.

The intensity of these costs depends on two factors. First, how and when do borrowers become aware of victimization. If they discover that they have been a victim relatively early following victimization, they may be able to resolve discrepancies in their credit reports prior to any credit demand shock and evade decline in credit access. Alternatively if it takes them a long time to uncover victimization, they may experience demand shocks before their reports have been resolved. Since an average borrower takes around 3 years to discover victimization, the costs in terms of lower credit access are likely to be substantial. Furthermore, because 26% of the borrowers in the sample discover that they have been a victim when they apply for credit, they are like to either be denied credit or pay more for it. Second, what happens when the borrowers attempt to recover from theft. While borrowers can report a fraud flag on their credit reports, any changes on the reported accounts need to come from the lenders. Usually lenders conduct their internal investigations when identity theft gets reported and only change their reporting of the accounts if their investigations conclude them to be fraudulent. From the victims' perspective, there is uncertainty regarding both the outcome and duration of such investigations.

4.2 Empirical approach

We employ a difference-in-differences approach to evaluate the association between identity fraud victimization and access to credit and financial distress. Our approach captures the relative changes in outcomes around victimization for victims compared to non-victim borrowers. However, instead of using a single dummy to capture the average difference between pre- and post-victimization, we split it into two components — one for the quarter of and one quarter following victimization and the other for all subsequent post periods. This allows us to capture the temporary abnormal jump in some variables that occurs at the time of victimization. Specifically, we estimate coefficients from the following specification.

$$y_{i,s,a,b,d,c,t} = \beta_1 \times Victimization\ I_{i,s,a,b,d,c,t} + \beta_2 \times Victimization\ II_{i,s,a,b,d,c,t} + \delta_i + \gamma_{s,t} + \Delta_{a,t} + \alpha_{b,t} + \theta_{d,t} + \mu_{c,t} + \epsilon_{i,s,a,b,d,c,t} \quad (1)$$

where y represents the outcome for individual i belonging to an ex-ante credit score decile c, age decide a, and total debt balance decile b with d number of delinquency and c accounts in collection during year-quarter t. $Victimization\ I$ is a dummy variable that takes a value of 1 for victim borrowers during the quarter of and one quarter post victimization and zero otherwise, and $Victimization\ II$ is a dummy variable that takes a value of 1 for victims during all quarters beginning the second quarter post victimization.

A potential concern with using a difference-in-differences approach in our setting is that there are ex-ante differences between victims and non-victims. To account for these differences, we saturate the model with a number of fixed effects. $\gamma_{s,t}$ represent credit score time effects that account for time varying differences across borrowers with different credit scores. Similarly $\Delta_{a,t}$ and $\alpha_{b,t}$ represent age and total debt balance time effects, and $\theta_{d,t}$ and $\mu_{c,t}$ represent fixed effects for number of delinquencies and collection accounts interacted with year-quarter. All control variables are measured one quarter prior to victimization and their interaction with time controls for any time varying differences across borrowers different along these dimensions. All specifications include individual fixed effects, δ_i, that control for time invariant differences at the borrower level. We cluster standard errors at the borrower level thereby allowing errors to be correlated for observations within the same borrower.

β_1 captures the change in the outcome variable for victims during the first two quarters of victimization and prior to victimization relative to the same change for non-victims. Similarly, β_2 captures this differential change between all periods from second quarter following victimization and those prior to victimization. The identifying assumption for this approach is that of parallel trends, i.e., controlling for all differences in our specification the residual variation in outcome variables between victim and non-victim borrowers trends parallelly if not for victimization. We rely on fixed effects to account for differences between victim and non-victim borrowers as it allows us to flexibly control for a number of dimensions non-parametrically. Using these many dimensions in a matching technique (e.g., propensity score) is likely to lead to inefficient matches.

To test the identifying assumption at least during the period prior to victimization, whether our controls account for ex-ante differences, and assess how outcomes evolve for borrowers following victimization, we also estimate the following dynamic specification:

$$y_{i,s,a,b,d,c,t} = \sum_{\substack{\tau=-9 \\ \tau\neq-8}}^{9} \beta_\tau \times Victimization_{i,s,a,b,d,c,\tau} + \delta_i + \gamma_{s,t} + \Delta_{a,t} + \alpha_{b,t} + \theta_{d,t} + \mu_{c,t} + \epsilon_{i,s,a,b,d,c,t} \quad (2)$$

where $Victimization_{i,s,a,b,d,c,\tau}$ are dummy variables that take a value of 1 for victim borrowers τ year-quarters before or after victimization. The omitted category is eight quarters before victimization and works as the base case for comparison. This specification allows us to plot the estimated coefficients β_τ with the corresponding confidence intervals. Each of these coefficients captures the association between victimization and outcome variables by event-quarter. Our sample consists of more than 8 quarters following and prior to victimization, so we include a dummy variable at both ends to capture all months before or after 8 quarters. Specifically, $\tau = 9$ and $\tau = -9$ capture all months after and before 8 quarters from victimization.

4.3 Results

4.3.1 Access to credit

Our first set of analyses focus on evaluating the association between victimization and access to credit. We begin by using account openings and change in credit balance as measures of credit access in regressions similar to those detailed in equation 1. Table 1 reports results for these tests with account openings as the outcome variable in panel A and change in credit balance in panel B. The estimates in column (1) of panel A show that there is a substantial increase in the number of account openings during the first two quarters of victimization and a decline in subsequent quarters relative to the period before victimization. The sharp increase during the quarter of victimization is by construction since fraudulent accounts open in the first quarter. This can spill over to the next quarter for two reasons. First, if multiple fraudulent accounts are opened in the victim's they may not all open during the same month. Second, there may be reporting delays from lenders depending on the type of account. The decline in subsequent quarters corresponds to borrowers opening 0.042 fewer accounts per quarter relative to quarters prior victimization. This decline is economically large as it corresponds to 100% of the mean number of new accounts opened per quarter in the sample. The other columns show consistent results across different types of credit suggesting that all of them contribute to the changes in overall balances.

Similar patterns emerge for changes in credit balance in panel B. While there is a mechanical sharp jump during the first two quarters of victimization, subsequent quarters experience a decline when compared to the period before victimization. This decline is economically large as it corresponds to 45% of the sample mean of the outcome. We next evaluate the differential trends between victims and non-victims in these outcomes around victimization using regressions similar to equation 2. Figure 4 plots these coefficients. Prior to victimization, both the number of account openings (panel (a)) and changes in credit balance (panel (b)) trend similarly across victims and non-victims. However, there is a sharp jump in the first two quarters of victimization and subsequent declines for victims relative to non-victim borrowers. The decline seems persistent with time lasting for at least 8 quarters.

4.3.2 Credit demand vs supply

New account openings and balances are equilibrium outcomes that can be driven by both credit supply and demand. While less likely, it is plausible that credit demand can change around victimization. For instance, if identity theft occurs immediately after an individual opens a new account, they may have less credit demand post victimization since they recently opened an account. We conduct several analyses to help disentangle supply and demand. Our data allows us to observe all credit inquiries made by potential lenders to evaluate credit applications. Since this captures credit demand, we can directly evaluate any changes in demand in our empirical setting. Panel (a) of Figure 5 plots coefficients of this analysis with the number of credit inquiries as the outcome variable in specification from equation 2. While there is a sharp temporary mechanical increase in the number of inquiries during the quarter of victimization and some spillover in the next quarter, there are no significant changes for subsequent quarters. This shows that credit demand does not change around victimization.

Notwithstanding this result, we redo our baseline analysis using two other measures of access to credit that are less likely to be subject to credit demand — credit score and credit denial. Table 3 reports estimates for this analysis. Column (1) shows the results for credit score as the outcome where we find a decline of about 3 points during the first two quarters of victimization and a decline of 10 points over the subsequent quarters. This decline is economically significant, and comparable to the effect of removing a bankruptcy flag reported by Dobbie et al. (2020). The authors find that credit scores exhibit respective increases of 9, 6, and 3 points in the first, second, and third years after flag removal, leading to large increases in credit limits and economically significant increases in borrowing. Looking at the dynamics of these associations, as reported in panel (a) of Figure 5 paints a similar picture. There are no differential trends between victims and non-victim borrowers during the period prior to victimization. However, there is a sudden decline following victimization that persists for over eight quarters.

We define credit denial as a dummy variable that takes a value of 1 during quarters when borrowers apply for credit (i.e., we observe an inquiry for their report) but no new accounts open in the given credit type. Columns (2)-(4) of Table 3 report estimates for analysis with credit denial across different credit types as outcome variables. While there is a jump in denials for the first two quarters of victimization, they remain elevated even in subsequent quarters. The economic magnitude is meaningful as it corresponds to an increase of 5.8% of the unconditional mean beginning two quarters following victimization. The dynamics of these associations reported in panel (c) of Figure 5 show a similar pattern with a sharp increase in denial during the quarter of victimization which remains elevated in subsequent quarters.

4.3.3 Financial distress

The results so far show a decline in access to credit likely owing to shrinking credit supply. We next examine whether this reduced supply has any implications for financial distress by evaluating incidences of distress events including bankruptcy filing, foreclosures, and delinquencies. Table 4 reports results for this analysis across three columns. We find that victimization is associated with a higher likelihood of distress for victims relative to non-victims across all three measures beginning two quarters following victimization. The economic magnitudes of these effects are meaningful and large as they correspond to a 64% increase in bankruptcy and 8% increase in foreclosure relative to the unconditional mean. The dynamics of these associations reported in Figure 6 show that both foreclosure and bankruptcy filings trend similarly for victims and non-victim borrowers in the period prior to victimization. However, victims are more likely to both be foreclosed upon and file for bankruptcy following victimization. Such financial distress events have long run repercussions as they are included in credit reports for up to 10 years following the event.

5 Conclusion

Financial fraud and scams are pervasive affecting millions of individuals every year in the U.S. While some types of fraud incur immediate pecuniary losses, long term costs and implications of fraud victimization remain unclear. This paper uses detailed micro-data to document the extent of financial fraud victimization, who becomes a victim, and the long-term costs of victimization. Our setting focuses on identity theft, one of the most common types of fraud comprising over 20% of all reported fraud in the U.S., to answer these questions.

Since little is known about identity fraud victimization, we first document several stylized facts relating to it including the extent and who becomes a victim. We find that credit profiles for over 26 million borrowers included a flag for being an identity theft victim between 2010 and 2022 (i.e., 8.7% of 306 million unique borrowers in the U.S.). More than six million of these borrowers simultaneously disputed at least one fraudulent account when they flagged that they have been victimized. While an average borrower disputed two fraudulent accounts, the average balance a victim owed on these accounts is $28,278. Most of these fraudulent accounts come from unsecured debt with credit cards comprising 50% of all fraudulent accounts and student loans comprising 14.4%. Low income, younger borrowers, and those with worse credit histories are more likely to become victims. While an average borrower takes three years to become aware that they have become a victim, over 26% of them find out when they apply for new credit.

We find considerable long term costs associated with fraud victimization. Victim borrowers have lower number of new accounts and balances relative to non-victim borrowers. These results are likely driven by a decline in access to credit rather than changes to credit demand. While the number of credit applications do not differentially change for victims, their credit scores relatively decline and credit denials increase and remain elevated for at least two years. The reduced credit access is accompanied by higher incidences of financial distress including bankruptcy filing, foreclosures, and delinquencies. Such financial distress events have long run repercussions as they are included in credit reports for up to 10 years following the event.

Heterogeneity analyses reveal that our results are stronger for borrowers with low ex-ante income and credit scores. Not only are low income borrowers more likely to become a victim but conditional on victimization they experience higher costs and decline in access to credit, thereby exacerbating the credit access gap over the income distribution.

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Figure 1:
Credit files with fraud flags over time
This figure plots the number of credit files that include a fraud flag over time.

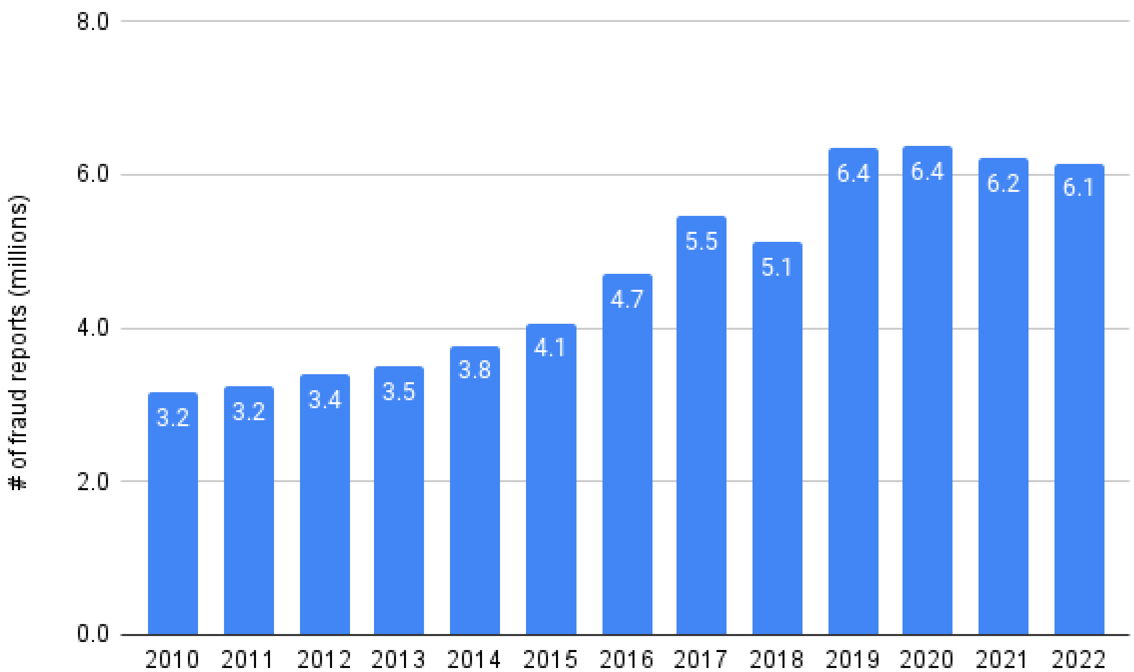


Figure 2:
Distribution of fraudulent account types

This figure shows the distribution of fraudulent accounts across different types of accounts/credit.

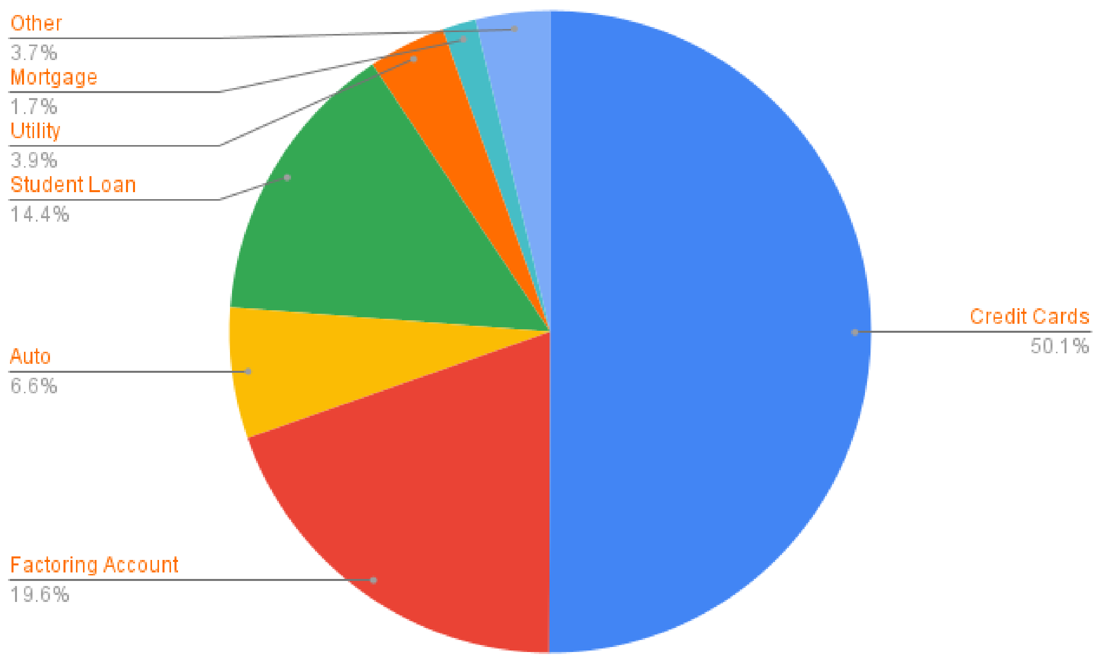
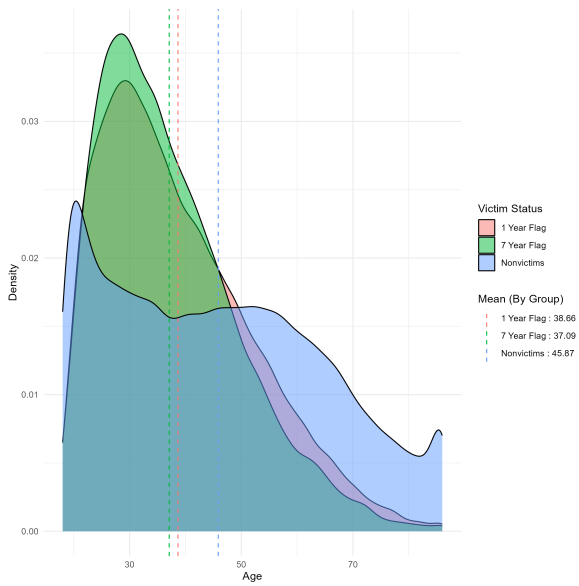
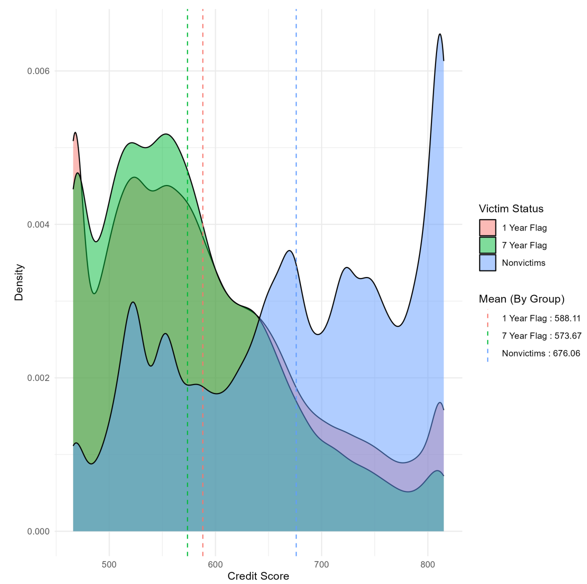


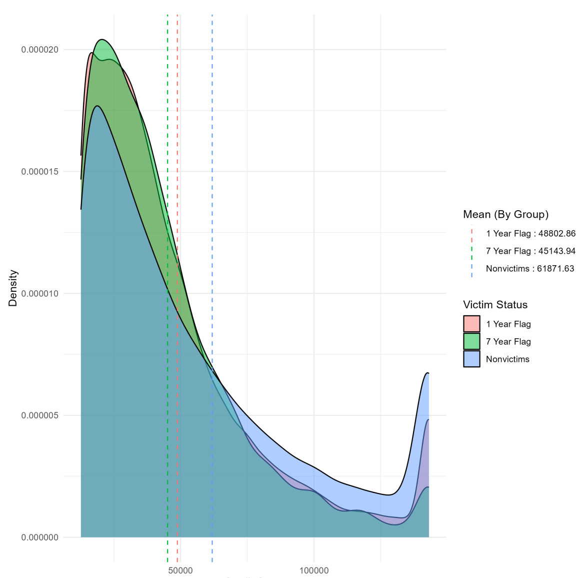
Figure 3:
Who becomes a victim?
This figure compares characteristics of identity theft victims to non-victim borrowers. Each panel shows density plots for the characteristic indicated in the sub-title for three different sub-groups: victims with 1 year fraud flag, those with 7 year fraud flag, and non-victim borrowers. The vertical lines highlight the means across these groups, which are also included in the legend.



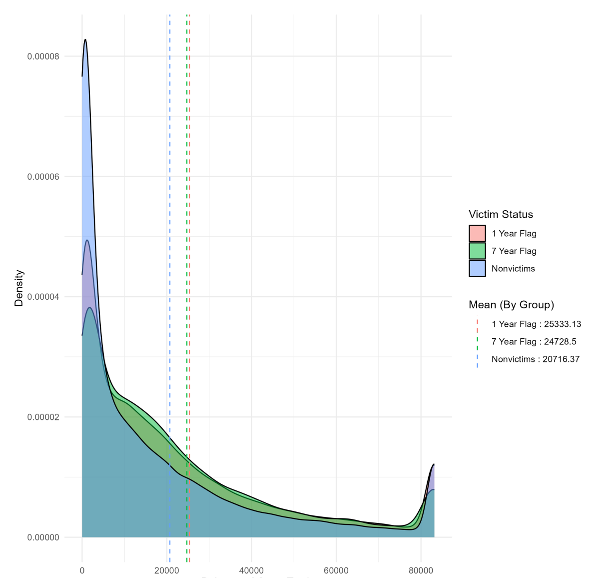
(a) Age



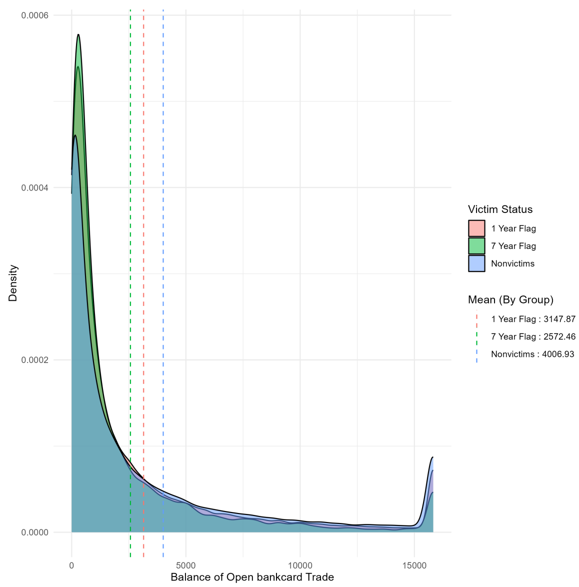
(b) Credit score



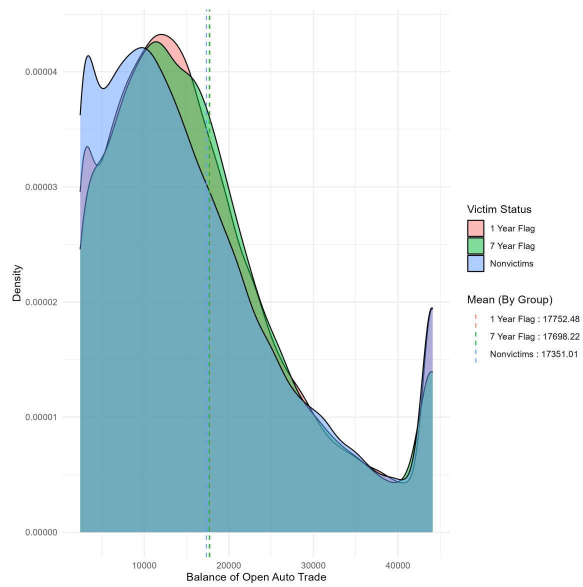
(c) Income



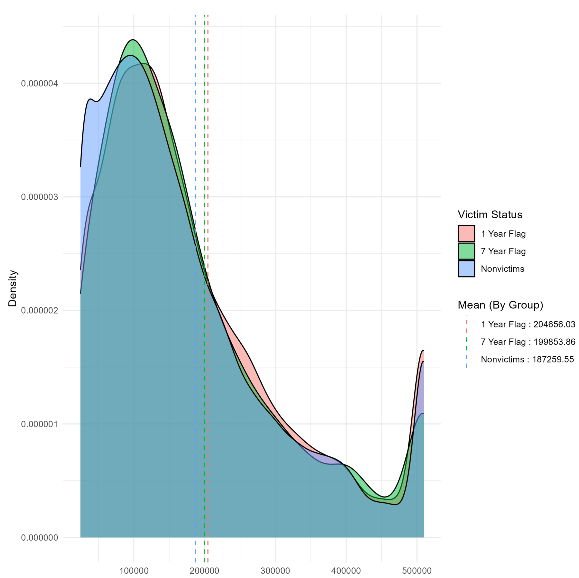
(d) Total debt balance



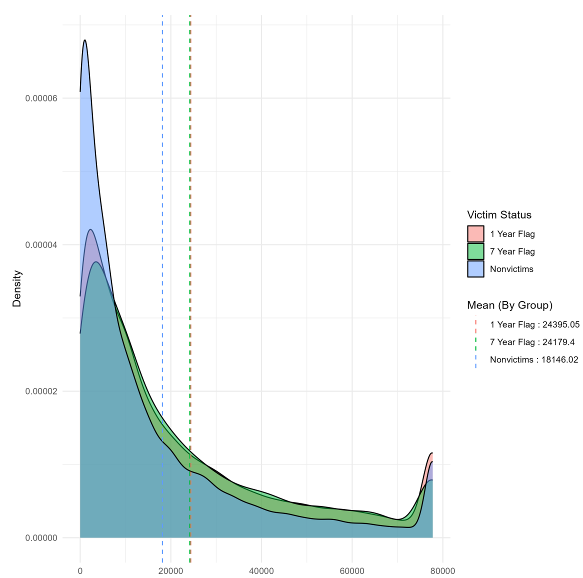
(e) Credit card balance



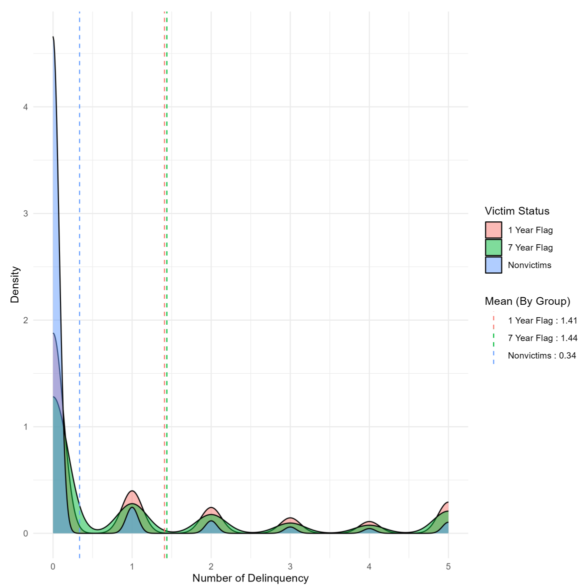
(f) Auto balance



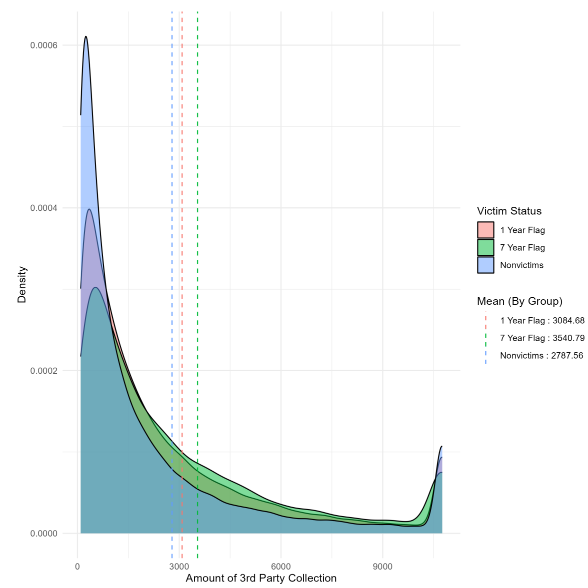
(g) Mortgage balance



(h) Student loan balance



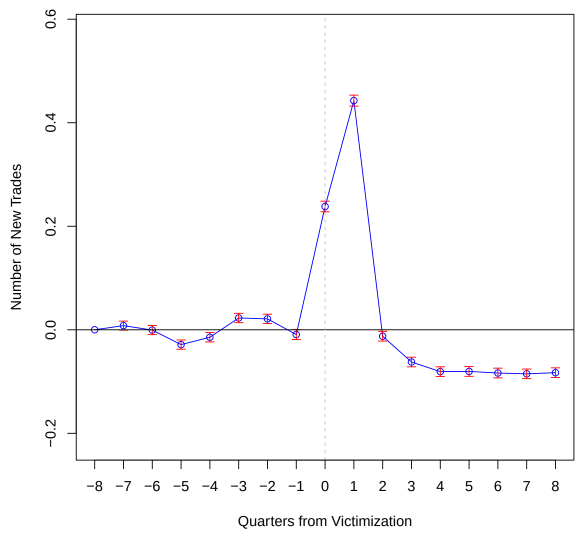
(i) Delinquencies



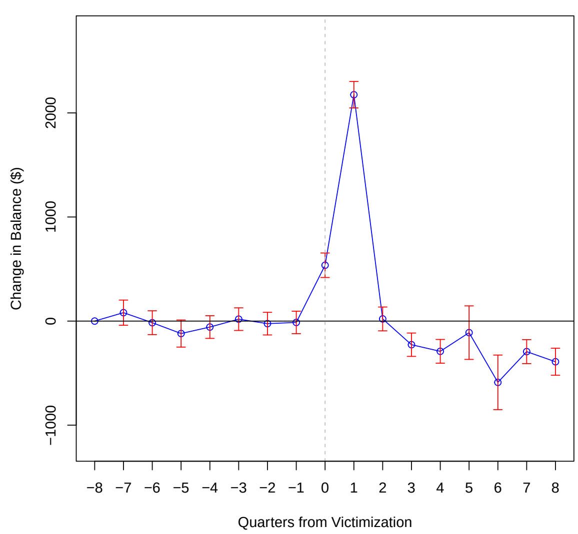
(j) Collections

Figure 4:
Access to credit

This figure plots estimates of the association between victimization and the outcome variable by event-quarter. The specification controls for a number of fixed effects as denoted in equation 2. The vertical lines represent intervals at 95% confidence. Standard errors are clustered at the individual level.



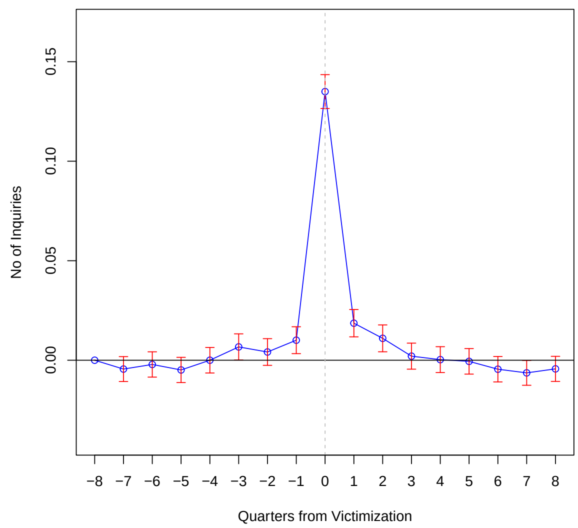
(a) Number of account openings



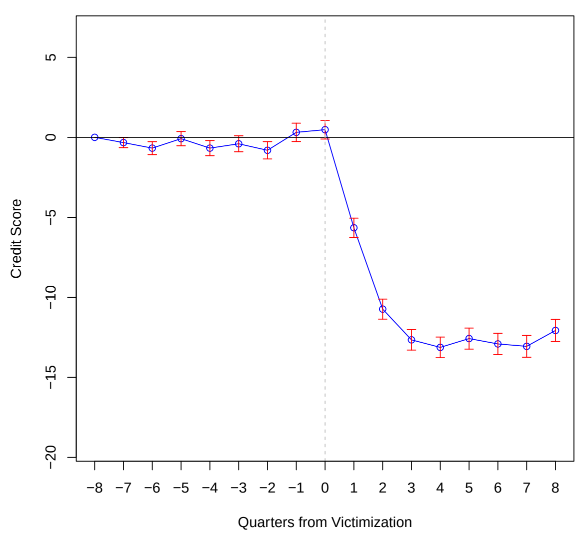
(b) Credit balance

Figure 5:
Credit demand vs supply

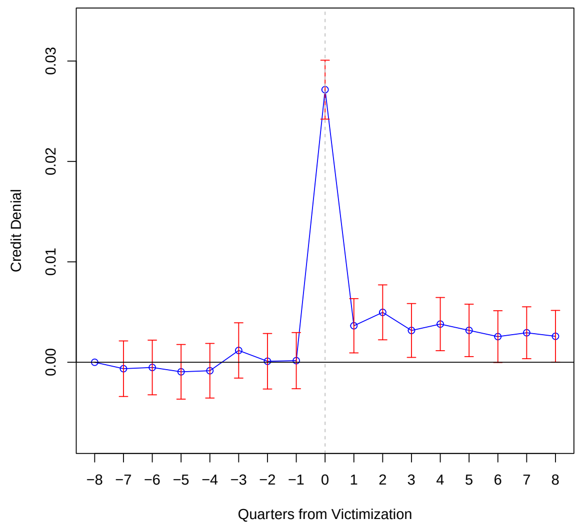
This figure plots estimates of the association between victimization and the outcome variable by event-quarter. The specification controls for a number of fixed effects as denoted in equation 2. The vertical lines represent intervals at 95% confidence. Standard errors are clustered at the individual level.



(a) Credit inquiries



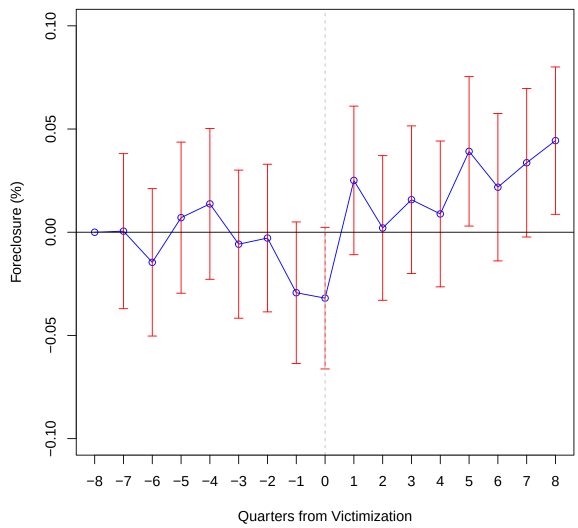
(b) Credit score



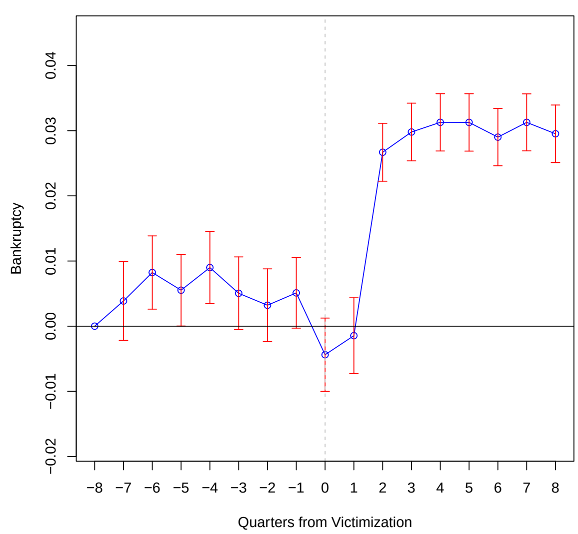
(c) Credit denial

Figure 6:
Financial distress

This figure plots estimates of the association between victimization and the outcome variable by event-quarter. The specification controls for a number of fixed effects as denoted in equation 2. The vertical lines represent intervals at 95% confidence. Standard errors are clustered at the individual level.



(a) Foreclosure



(b) Bankruptcy

Table 1:
Access to credit
This table reports the estimates for the analysis that evaluates the association between identity fraud victimization and account openings in panel A and victimization and changes in credit balance in panel B. Different columns in both panels capture the outcome variables for different types of credit. The specification controls for a number of fixed effects as denoted in each column. Standard errors are clustered at the individual level and reported in parentheses below the estimates. ***, **, and * represent significance at 10%, 5% and 1% levels.

Panel A

	Number of account openings			
	All	Auto	Mortgage	Student Loan
	(1)	(2)	(3)	(4)
Victimization I	0.346***	0.023***	0.001***	0.013***
	(0.003)	(0.001)	(0.0002)	(0.002)
Victimization II	−0.042***	−0.004***	-0.0004***	−0.003***
	(0.001)	(0.0002)	(0.0001)	(0.001)
Individual FE	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes
Observations	14,355,342	14,355,342	14,355,342	14,355,342
R^2	0.026	0.005	0.045	0.018

Panel B

	Credit balance			
	All	Auto	Mortgage	Student Loan
	(1)	(2)	(3)	(4)
Victimization I	1,431.663***	479.140***	96.229*	59.930***
	(31.238)	(14.376)	(51.677)	(10.945)
Victimization II	−153.397***	−39.561***	-74.607***	−1.650
	(15.218)	(5.517)	(28.154)	(6.103)
Individual FE	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes
Observations	10,400,069	10,400,069	10,400,069	10,400,069
R^2	0.010	0.011	0.010	0.015

Table 3:
Credit supply

This table reports the estimates for the analysis that evaluates the association between identity fraud victimization and access to credit as measured by credit score and denials. While column (1) shows results for credit score, other columns report them for credit denials by the type of account. The specification controls for a number of fixed effects as denoted in each column. Standard errors are clustered at the individual level and reported in parentheses below the estimates. ***, **, and * represent significance at 10%, 5% and 1% levels.

	Credit score	Credit denial		
		All	Auto	Mortgage
	(1)	(2)	(3)	(4)
Victimization I	-2.978^{***}	0.012^{***}	0.020^{***}	0.009^{***}
	(0.171)	(0.0005)	(0.001)	(0.0003)
Victimization II	-10.003^{***}	0.002^{***}	0.002^{***}	0.002^{***}
	(0.199)	(0.0002)	(0.0003)	(0.0002)
Individual FE	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes
Observations	13,635,852	14,331,785	14,127,864	13,849,585
R^2	0.805	0.102	0.120	0.090

Table 4:
Financial distress

This table reports the estimates for the analysis that evaluates the association between identity fraud victimization and financial distress as measured bankruptcy filings, foreclosure, and delinquency. The specification controls for a number of fixed effects as denoted in each column. Standard errors are clustered at the individual level and reported in parentheses below the estimates. ***, **, and * represent significance at 10%, 5% and 1% levels.

	Bankruptcy	Foreclosure	Delinquency
	(1)	(2)	(3)
Victimization I	-2.223^{***}	0.002	0.444^{***}
	(0.137)	(0.009)	(0.057)
Victimization II	1.726^{***}	0.011^{**}	2.230^{***}
	(0.050)	(0.006)	(0.038)
Individual FE	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes
Observations	14,040,156	14,355,342	14,040,156
R^2	0.027	0.033	0.080

Table 5:

Heterogeneity by income and credit score

This table reports the estimates for the analysis that evaluates the heterogeneity in association between identity fraud victimization and our main outcomes. Panel A reports heterogeneity by income and panel B reports it by credit score. The specification controls for a number of fixed effects as denoted in each column. Standard errors are clustered at the individual level and reported in parentheses below the estimates. ***, **, and * represent significance at 10%, 5% and 1% levels.

Panel A: Income

	Balance	Balance	Denial	Denial	Bankruptcy	Bankruptcy
	(1)	(2)	(3)	(4)	(5)	(6)
Victimization I	1,194.404***	1,692.179***	0.013***	0.012***	−1.157**	−0.154
	(63.549)	(124.586)	(0.002)	(0.002)	(0.465)	(0.181)
Victimization II	−249.067***	−171.456***	0.003***	0.002***	2.714***	−0.257***
	(32.859)	(53.192)	(0.001)	(0.001)	(0.201)	(0.092)
Sample	Low	High	Low	High	Low	High
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	789,934	912,656	1,025,392	1,027,231	1,004,871	1,007,293
R^2	0.011	0.008	0.110	0.097	0.033	0.031

Panel B: Credit score

	Balance	Balance	Denial	Denial	Bankruptcy	Bankruptcy
	(1)	(2)	(3)	(4)	(5)	(6)
Victimization I	963.027***	2,257.858***	0.012***	0.013***	2.554***	0.716***
	(30.057)	(67.090)	(0.001)	(0.001)	(0.080)	(0.151)
Victimization II	−238.532***	−73.331***	0.002***	0.001***	1.833***	1.538***
	(17.314)	(26.147)	(0.0003)	(0.0003)	(0.060)	(0.072)
Sample	Low	High	Low	High	Low	High
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,583,600	5,683,423	6,811,145	6,844,503	6,684,572	6,703,440
R^2	0.013	0.008	0.108	0.073	0.014	0.030

Table 6:
Controlling for ex-ante income
This table reports the estimates for the analysis that evaluates the association between identity fraud victimization and individual-level outcomes. Different panels correspond to different outcomes namely access to credit (panels A and B), credit supply (panel C), and financial distress (panel D). The specification controls for a number of fixed effects as denoted in each column. Standard errors are clustered at the individual level and reported in parentheses below the estimates. ***, **, and * represent significance at 10%, 5% and 1% levels.

Panel A

	Number of account openings			
	All	Auto	Mortgage	Student Loan
	(1)	(2)	(3)	(4)
Victimization I	0.342***	0.026***	0.003***	0.001
	(0.008)	(0.001)	(0.0005)	(0.005)
Victimization II	−0.047***	−0.005***	-0.001**	−0.006***
	(0.003)	(0.001)	(0.0003)	(0.002)
Individual FE	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes
Income x Year-month FE	Yes	Yes	Yes	Yes
Observations	2,055,752	2,055,752	2,055,752	2,055,752
R^2	0.025	0.006	0.046	0.019

Panel B

	Credit balance			
	All	Auto	Mortgage	Student Loan
	(1)	(2)	(3)	(4)
Victimization I	1,426.085***	569.178***	133.294	−18.220
	(68.097)	(29.439)	(109.920)	(26.406)
Victimization II	−212.091***	−33.561***	−24.289	−20.609
	(32.003)	(11.527)	(64.911)	(15.246)
Individual FE	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes
Income x Year-month FE	Yes	Yes	Yes	Yes
Observations	1,702,590	1,702,590	1,702,590	1,702,590
R^2	0.008	0.012	0.010	0.007

Panel C

	Credit score	Credit denial		
		All	Auto	Mortgage
	(1)	(2)	(3)	(4)
Victimization I	-1.459^{***}	0.013^{***}	0.023^{***}	0.009^{***}
	(0.396)	(0.001)	(0.001)	(0.001)
Victimization II	-8.733^{***}	0.002^{***}	0.001^{*}	0.002^{***}
	(0.466)	(0.001)	(0.001)	(0.0005)
Individual FE	Yes	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes	Yes
Income x Year-month FE	Yes	Yes	Yes	Yes
Observations	2,029,751	2,052,623	2,021,293	1,965,780
R^2	0.789	0.103	0.123	0.093

Panel D

	Bankruptcy	Foreclosure	Delinquency
	(1)	(2)	(3)
Victimization I	-0.796^{***}	-0.004	0.083
	(0.270)	(0.020)	(0.141)
Victimization II	1.271^{***}	-0.007	2.114^{***}
	(0.112)	(0.013)	(0.098)
Individual FE	Yes	Yes	Yes
Credit score x Year-month FE	Yes	Yes	Yes
Age x Year-month FE	Yes	Yes	Yes
Balance x Year-month FE	Yes	Yes	Yes
Delinquency x Year-month FE	Yes	Yes	Yes
Collections x Year-month FE	Yes	Yes	Yes
Income x Year-month FE	Yes	Yes	Yes
Yes			
Observations	2,012,164	2,055,752	2,012,164
R^2	0.032	0.034	0.079