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ABSTRACT

We examine how a negative shock from severe identity theft affects consumer credit market behavior in the United States. We show that the immediate effects of severe identity theft on credit files are typically negative, small, and transitory. After those immediate effects fade, identity theft victims experience persistent increases in credit scores and declines in reported delinquencies, with a significant proportion of affected consumers transitioning from subprime-to-prime credit scores. Those consumers take advantage of their improved creditworthiness to obtain additional credit, including auto loans and mortgages. Despite having larger balances, these individuals default on their loans less than they did prior to the identity theft incident.

Keywords: identity theft, fraud alert, consumer credit, credit performance, limited attention, inattention

JEL Codes: G5, D14, D18

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1. Introduction

Recent major data breaches and numerous smaller scale data losses regularly subject the sensitive personal information of hundreds of millions of consumers around the world to potential criminal use, including identity theft. Such personal information may include consumer names, dates of birth, or Social Security numbers (SSNs) as well as trade-level data for financial accounts. In the United States, the prevalence and magnitude of identity theft has been widely documented and publicized in recent years. The U.S. Bureau of Justice Statistics (BJS) reported that in 2016, 26 million U.S. consumers (about 10 percent of adults) were victims of at least one incident of identity theft. These victims reported gross financial losses of approximately $17.5 billion (Harrell, 2019) and experienced significant emotional distress owing to the fraud.[1]

A disproportionate share of fraud-related losses is attributable to victims of severe identity theft — consumers who experienced an identity theft incident that involved the opening of new accounts or the misuse of their personal information. Severe identity theft victims represent one-tenth of identity theft victims but bear over half the out-of-pocket (OOP) costs of identity theft in the United States. Despite the prevalence of identity theft, little is known about the consequences of severe identity theft for individual consumers or about consumers' response to such burdensome forms of identity theft, particularly in the context of their credit behavior.

We contribute new insights on the effects of severe identity theft on consumer credit outcomes by assembling a new, unique data set combining anonymized consumer credit records from a major U.S. credit bureau with information about fraud alerts that consumers can file following incidents of identity theft. We focus on those individuals who place an extended fraud alert in their credit bureau files, as they are the group of consumers that most closely proxy for victims of severe identity theft. Based on data from the National Crime Victimization Survey's (NCVS) Identity Theft Supplement, victims of severe identity theft are nine times more likely to file an extended fraud alert compared with other identity theft victims, and extended alert filers are six times more likely to be victims of severe identity theft (42 percent) compared with victims who did not file an alert (7 percent). In addition, extended alert filing procedures require fraud victims to provide extensive evidence of identity theft (under penalty for misrepresenting this information), such that extended alerts are extremely unlikely to be purely precautionary in nature.

[1] Net losses for consumers are much less frequent and typically small in magnitude. Harrell (2019) is based on the Identity Theft Supplement to the National Crime Victimization Survey (NCVS), which is a nationally representative survey of individuals' experience with crime in the U.S. conducted by the U.S. Bureau of Justice Statistics (BJS). For detailed information on the NCVS and its methodology, visit https://www.bjs.gov/index.cfm?ty=dcdetail&iid=245.

Severe identity theft victims represent particularly interesting subjects for a study of consumer credit outcomes. Based on information from the NCVS, these consumers tend to have lower incomes, are non-White, and suffer from employment disruptions more frequently (making them more vulnerable to identity theft). Therefore, these individuals are more likely to suffer as a result of identity theft, for example, taking a longer time and expending more effort to resolve fraud and/or being more likely to experience monetary losses or physical/mental health issues. They may also be less prepared to deal with the stressful consequences of identity theft.[2] We consider it crucial to understand the impact of an adverse financial shock like severe identity theft on how consumers interact with credit markets, especially since severe identity theft affects more vulnerable consumers.

To explore the effect of severe identity theft on consumer credit outcomes, we use an anonymized 5 percent random sample of quarterly credit records of U.S. consumers from the credit bureau Equifax, supplemented with additional data detailing the timing (placement) and type of fraud alerts that the consumers filed. We restrict our sample to the approximately 50,000 consumers who filed an extended fraud alert (and therefore experienced severe identity theft) between Q1:2008 and Q3:2013 and observe their credit history for several years before and after the fraud incident. Given the quarter-by-quarter nature of how the data are collected for our data set, all potentially fraudulent credit activity (including new accounts or balance increases) is reflected in the data for us to detect in our analysis. To identify the effect of severe identity theft on consumer credit outcomes, we use the plausibly exogenous timing of fraud occurrence and formulate an event-study methodology, comparing victimized consumers with not-yet-victimized consumers who are arguably similar along unobservable characteristics.

With our data and identification strategy, we provide evidence on three broad research questions. First, we examine the immediate effect of severe identity theft on consumer credit outcomes shortly before and during victimization (as proxied by extended fraud alert filing). Second, we examine consumer credit outcomes after the immediate effects of severe identity theft are removed. Third, we provide evidence of long-term consequences of severe identity theft on consumer creditworthiness, borrowing, repayment, and loan default.

For the first question, we document that severe identity theft leads to additional credit inquiries (applications for credit) in victims' credit files, new credit cards opened in their name, and an abnormal rate of reverse address changes (reversals of a temporary address change to the original address). These changes are consistent with criminals applying for credit with stolen consumer information, being approved for new credit cards using the stolen information to impersonate actual consumers, and

[2] Additionally, our findings can be viewed as an upper bound for the likely effects of milder forms of identity theft in the United States, particularly as less severe fraud is more likely to fall under the zero liability credit card rules and be resolved quickly in the consumer's favor.

deceiving lenders into sending these cards to new addresses where criminals can collect them. These fraudulent activities negatively affect consumers' overall credit standing as represented by the Equifax Risk Score (Risk Score), a form of credit score.[3] The Risk Score of severe identity theft victims declines by 4 points, on average, relative to the group of victims who have not yet been victimized, with some consumers experiencing larger Risk Score declines and becoming subprime as a result of the fraud.

Second, we find that many of the negative consequences of severe identity theft observed immediately upon impact quickly disappear from credit bureau records. In particular, credit inquiries, the number of new credit cards, and address reversals all decrease significantly and quickly. Further, we observe positive changes to consumer credit attributes initially unaffected by fraud. For example, we observe significant and persistent reductions in the number of accounts in third-party collections and major derogatory events, while the share of card balances in good standing increases. The removal of fraudulent information from affected individuals' credit bureau files alone is insufficient to explain these incremental positive changes.

Consistent with the improvements in individual credit characteristics, we find that severe identity theft victims' Risk Scores increase by an average of 10 points after the immediate effects of identity theft fade. For many of these consumers, this Risk Score increase is larger than the decrease in the Score due to fraud (4 points, on average). We also observe that the proportion of fraud victims with prime Scores increases by 5 percentage points (a relative 11 percent increase) after filing an extended fraud alert, which is a substantial shift in the Risk Score distribution. Becoming a prime consumer carries substantial economic benefits, as previous studies have shown that prime borrowers are more likely to be approved for credit and tend to receive better terms of credit (e.g., lower annual percentage rates), even for marginal consumers.

We also document that many consumers appear to use their improved creditworthiness after severe identity theft to apply for additional credit. In particular, we find that consumers apply for new auto loans and increase both the number of such loans and balances on them. Similarly, some of these consumers apply for new mortgages, have more mortgages, and increase overall mortgage balances. Despite having additional mortgage and auto loans and increased balances on them, consumer performance on these loans is as good as or better than before identity theft. These findings are particularly pronounced for the group of consumers most likely to benefit from improved creditworthiness — those who transitioned from subprime Risk Scores before fraud to having prime Scores after fraud.

[3] We use the term *Risk Score* or *Score* to refer to a proprietary credit score provided to us by Equifax. Subprime borrowers are defined as those with Scores less than or equal to 660, while prime borrowers have Scores above 660.

While we cannot definitively rule out alternative mechanisms that may explain the short-run impact of severe identity theft on credit attributes, we provide strong evidence that consumer inattention to credit reports is the most plausible explanation for the patterns in consumer credit attributes that we observe. The short-run improvements in Risk Scores, major derogatory events, collection accounts, and card balances in good standing suggest that many severe identity theft victims were not actively scrutinizing their credit reports prior to their victimization. The fact that many of these attributes improved more than they deteriorated on impact suggests that consumers were not aware of preexisting errors in their reports and corrected those shortly after being victimized. Our explanation is consistent with the finding that individuals do not pay attention to their credit reports, which in turn can lead to errors in credit files persisting (e.g., Federal Trade Commission (2012) finds that 26 percent of consumers have material errors in their credit reports and 13 percent experienced credit score changes after the errors were corrected). Specifically, the persistent improvement in the management of open accounts for the severe identity theft victims in our sample suggests that consumers are more attentive to their credit than they were before they were victimized. Our results should be interpreted with caution, however, as they are most applicable to *severe identity theft victims* and may not be generalizable to all identity theft victims as the salience of the fraud-related information may not be as pronounced for milder fraud experiences.

The finding that some victims of severe identity theft use their improved creditworthiness to apply for new credit is consistent with prior studies showing that consumers apply for credit after positive shocks to their credit scores.[4] We contribute to this literature by showing a similar tendency among a population of severe identity theft victims. We also document that the credit expansion does not lead to additional defaults in the long run for this consumer population. This finding is in contrast to some prior studies of credit expansions under different circumstances (e.g., Musto (2004) finds that borrowers are more likely to default on credit obtained after a bankruptcy flag removal, thus suggesting that this removal results in a loss of important information). Overall, our findings imply that, even for a consumer population with more severe identity theft and OOP losses, identity theft is not likely to lead to long-term credit damage or consumer withdrawal from credit markets. On the contrary, identity theft events may serve as a *teachable moment* for consumers who were previously not knowledgeable about credit bureau records or consumer credit markets more broadly.

[4] For example, Gross, Notowidigdo, and Wang (2020) show that borrowing on cards, auto loans, and mortgages rises after credit score increases following bankruptcy flag removals. Similar effects are documented by Musto (2004); Bos, Breza, and Liberman (2018); Herkenhoff, Phillips, and Cohen-Cole (2018); and Dobbie et al. (2020).

2. Contributions to the Literature

This paper contributes to several existing literatures. First, our paper relates to a large and growing literature showing that individuals in a variety of contexts pay limited attention to and do not process information completely when making important decisions. Previous work has demonstrated that investors react less than optimally to information readily available to them at no cost (Barber and Odean, 2008; DellaVigna and Pollet, 2009; Hirshleifer, Lim, and Teoh, 2009, 2011), that consumers either forget or fail to incorporate relevant consumption-related decisions (Grubb, 2015; Lacetera, Pope, and Sydnor, 2012), and that providing relevant information to consumers may increase attention and improve financial outcomes (Stango and Zinman, 2014; Bracha and Meier, 2015). Our work is also closely associated to the theoretical work on inattention and salience (DellaVigna, 2009; Gabaix and Laibson, 2000, 2001; Gabaix et al., 2006; Bordalo, Gennaioli, and Shleifer, 2013a, 2013b). We add to this broad literature by showing that severe identity theft may serve as a salient, negative event that reminds consumers to check credit reports, correct any errors, and potentially exhibit care and attention to their credit.

Second, our paper contributes to the literature on fraud in financial markets. While much of this literature focuses on the parties that commit fraud, such as financial advisors (Dimmock, Gerken, and Graham, 2018; Dimmock and Gerken, 2012; Egan, Matvos, and Seru, 2019; Qureshi and Sokobin, 2015), CEOs (Khanna, Kim, and Lu, 2015; Agrawal, Jaffe, and Karpoff, 1999), and firms (Piskorski, Seru, and Witkin, 2015; Povel, Singh, and Winton, 2007; Dyck, Morse, and Zingales, 2010, 2014), we examine the effects of fraud on victims' credit outcomes. Our study complements research on the effects of fraud on investment decisions by individuals and households (Gurun, Stoffman, and Yonker, 2018; Giannetti and Yang, 2016). We add to these studies by showing evidence of the effects of severe identity theft on consumer borrowing decisions in credit markets.

Third, our empirical findings add to the literature that examines the consequences of identity theft on consumers. However, unlike previous studies that focused on consumer confidence in payment systems (e.g., Sullivan, 2010) and payment choice (Cheney et al., 2012; Kahn and Liñares-Zegarra, 2016; Stavins, 2013; Kosse, 2013), this paper examines how severe identity theft can affect consumers' credit performance and credit outcomes. This study is also related to papers considering the tradeoff between information security and data privacy (Acquisti, 2004; Anderson and Moore, 2007) and incentives for consumers to prevent identity theft (Federal Trade Commission, 2003; Cheney, 2003).

3. Consumer Credit Bureau Records and Identity Theft in the United States

3.1 Information Contained in Consumer Credit Bureau Records

In this paper, we examine the financial consequences of identity theft on consumer credit attributes and subsequent consumer use of their improved creditworthiness using detailed, anonymized, credit bureau records from a major U.S. credit bureau. In the United States, a consumer credit report (also referred to as credit file) is an organized record of an individual's interaction with the credit market. Typically, a report will include information on the number, size, age, composition, and repayment status of the consumer's loans or lines of credit. A credit report may also include information obtained from public records, such as bankruptcy filings. In the United States, the three largest credit reporting agencies with national scope are Equifax, Experian, and TransUnion.

3.2 Extended Fraud Alerts

In 2003, the Fair and Accurate Credit Transactions Act (FACTA) became law, amending the Fair Credit Reporting Act (FCRA) of 1970. One of the goals of FACTA was to improve protection for consumers affected by identity theft. FACTA permitted consumers to obtain free copies of their credit reports from each of the three major bureaus once per year. FACTA also required federal regulators to develop *red flag* indicators of identity theft to aid in detecting fraud. It also required credit reporting agencies to block information that results from identity theft and to implement a set of indicators (credit file flags) that inform creditors that a consumer was, or may have been, a victim of identity theft. The credit file flags include extended fraud alerts that we use in this paper.

The elaborate process of filing for an extended fraud alert implies that practically all filers of extended alerts have been victims of severe identity theft, rather than acting out of precaution. In particular, extended fraud alert filers must submit a police report or an Identity Theft Report to place the alert in their credit bureau files. An Identity Theft Report requires detailed information on the accounts that were compromised and accompanying evidence of identity theft or fraud. Providing such evidence requires both time and effort. In addition, consumers face criminal penalties for falsifying information in these reports.[5] Thus, filers of extended alerts are actual victims of identity theft — in particular, as we will

[5] FACTA, §111, defines an *Identity Theft Report* as, at a minimum, "a report that alleges an identity theft; that is a copy of an official, valid report filed by a consumer with an appropriate Federal, State, or local law enforcement agency, including the United States Postal Inspection Service, or such other government agency deemed appropriate by the Federal Trade Commission; and the filing of which subjects the person filing the report to criminal penalties related to the filing of false information if, in fact, the information in the report is false."

show, severe identity theft — and are unlikely to place alerts in their credit bureau files simply because of worry, out of an abundance of caution, or for a related reason.[6]

After an Identity Theft Report or a police report has been filed, the consumer can add an extended fraud alert to his or her credit report. Extended fraud alerts require a creditor to take additional steps in verifying the consumer's identity when a request is made to open a new credit account, increase an existing credit line, or issue an additional card associated with an existing credit account. The consumer specifies a telephone number or other reasonable contact method as part of the alert documentation. All creditors must contact the consumer by the method specified in the alert to verify the consumer's identity in the case of any of the applicable scenarios. Once filed, an extended fraud alert remains in a consumer's credit file for seven years unless the consumer chooses to remove it earlier than that. In addition, an extended fraud alert removes the consumer's credit file from lists of prescreened credit and insurance offers for five years. Under FACTA, when a consumer files an alert with one national credit bureau, the information submitted by the consumer is communicated to the other two major bureaus.

An important element of the rights established in FACTA (and some state laws) is the opportunity for the consumer to obtain a copy of his or her credit report at no cost from each of the three credit bureaus when filing a fraud alert, including an extended fraud alert. Receiving these reports gives consumers a chance to detect and dispute fraudulent accounts or delinquencies on compromised accounts as well as any other errors in their credit reports. If the information in a consumer's credit report cannot be verified by the creditor, the credit bureaus are required to remove this information and to prevent it from reappearing in subsequent reports. It is important to note that requesting a credit report or filing a fraud alert by itself does not remove fraudulent charges from credit accounts with individual creditors and does not prevent data on already open but not-yet-disputed fraudulent accounts from being added to the credit report. Even after filing an alert, consumers need to identify fraudulent information and dispute this information.

4. Data Description

To explore the effect of identity theft on consumer credit, we use the Federal Reserve Bank of New York Consumer Credit Panel/Equifax Data (CCP), combined with a unique data set detailing the timing (placement) and type of fraud alerts that the Consumer Finance Institute obtained from Equifax. The CCP contains credit characteristics for an anonymized 5 percent random sample of credit bureau records of

[6] Later in the paper, we confirm this by examining the prevalence of different types of fraud alerts in our credit bureau sample and in the largest and nationally representative survey of identity theft victims, the National Crime Victimization Survey (NCVS) administered by the Bureau of Justice Statistics.

U.S. consumers.[7] The CCP is an unbalanced panel in which new individuals are included over time as they obtain or first report an SSN to a lender (e.g., after immigrating to the United States), open their first credit accounts, or establish their first public record. Similarly, consumers are dropped from the sample when they die, change their SSNs, or "age off" following a prolonged period of inactivity and no new items of public record. The sample is designed to produce a panel with entry and exit behavior similar to the population that uses credit or has a credit history (Lee and van der Klaauw, 2010).

We begin with a sample of credit files of about 10.8 million individuals continuously present in the data set in all quarters from Q1:2008 to Q3:2013 so that we can trace the credit histories of these consumers and mitigate concerns about "fragments" in our data (Wardrip and Hunt, 2013). We then restrict our sample to 52,649 consumers who filed an extended fraud alert (and therefore experienced severe identity theft) between Q1:2008 and Q3:2013 and observe their credit history for several years before and after the fraud incident.[8] In much of the following analysis, we examine changes in consumer credit attributes in *event time* — the number of quarters before or after an extended fraud alert first appears.

Within the CCP, we have access to rich consumer-level information on mortgage accounts, home equity revolving accounts, auto loans, bankcard accounts, student loans, and other loan accounts as well as public record and collection agency data. The CCP contains limited personal background information, such as the consumer's age and geographic information in the form of a scrambled address, state, zip code, metropolitan statistical area, and U.S. Census tract and block. We also have a credit score (specifically, the Equifax Risk Score) and the number of inquiries (i.e., applications for credit or insurance). To understand how severe identify theft affects consumers' use of credit, we examine the number of and balances on revolving accounts, the proportion of cards in good standing, total credit card limit, and many other consumer characteristics for several quarters before and after identity theft. Table 1 presents the descriptive statistics for the sample of extended alert filers in our data set.

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[7] The sample is constructed by selecting consumers with at least one public record or one credit account currently reported and a few random combinations of the last two digits of their SSNs as the method of randomly selecting the sample. Equifax uses SSNs to assemble the data set, but the actual SSNs are not shared with researchers. In addition, the data set does not include any names, actual addresses, demographics (other than age), or other codes that could identify specific consumers or creditors. Our data on fraud alerts span Q1:2008 to Q3:2013.

[8] It is important to emphasize that our analysis sample consists of consumers who *filed* their extended fraud alert during our sample period. Once an extended alert is filed, it is present in the credit file for many years, so we need to distinguish between the quarter in which the alert is placed in the file and the subsequent quarters during which the alert is active. As discussed later, our sample is designed to capture consumers around the time they experience identity theft, so we focus on consumers who *filed* an extended fraud alert during our sample period, not the larger group of consumers who have an extended fraud alert in their credit file.

4.1 Timing and Evidence of Fraud Removal

FACTA requires that U.S. credit reporting agencies block information resulting from identity theft four days after accepting a consumer's dispute identifying this information. The agencies must notify information furnishers (lenders, servicers, etc.) that the information they submitted will be blocked from the consumer's credit file. This notification triggers actions required by FACTA for furnishers of the information, including that the furnisher may not continue to report this information to any credit reporting agency. Another option available to all consumers, not just identity theft victims, through the FCRA is the right to dispute errors (inaccurate or incomplete information) in credit reports. When such a dispute is verified, it may result in a change to or deletion of information in a consumer's credit report.

We cannot directly observe what kind of information is blocked or for what reasons. However, the manner in which each quarter of the CCP data is assembled implies that any fraud existing in the quarters *preceding* the filing of an extended fraud alert remains in the data. That is because, generally speaking, when a new quarter of data is added to the CCP, the information contained in the previous quarters is not revised. In this sense, this data set is similar to other real-time data sets used by researchers. It is important to emphasize that this property of our data does not necessarily apply to the actual credit report information that consumers and creditors access every day. When an error is discovered in information contained in those credit bureau files, the erroneous information no longer appears anywhere in the credit history that a consumer or a creditor can see.[9] We use this specific nature of the CCP to detect evidence of both identity theft and its resolution in consumer credit attributes, as discussed in the next sections.

5. Research Design

5.1 Identification Strategy

To identify the effects of severe identity theft on consumer credit outcomes, we exploit two key features of our data that allow us to obtain causal estimates for victims of particularly severe forms of identity theft.

First, we rely on plausibly exogenous variation in the timing of identity theft victimization for consumers in our data. This strategy can address the possible obstacle of endogenous selection into

[9] It is possible that the timing of the placement of extended fraud alerts may not coincide perfectly with changes in credit variables. For example, consumers who file their alerts at the end of the third month of a quarter may not have their credit file updated until the first month of the following quarter. We considered the changes in key credit variables across event time by the month of extended alert filing to address this concern. Our results (available in Appendix Figure A15) indicate that both the timing of fraud and the effect of placement of fraud alerts do not systematically differ by the filing month.

identity theft and extended alert filing. Ideally, to identify the direct effects of fraud, we would compare identity theft victims with a comparable group of nonvictims. However, since identity theft victimization and extended alert filing may be endogenous, such an approach is not possible. To account for any potential selection on observable or unobservable characteristics, we propose an identification strategy that relies on the variation in the timing of victimization and extended alert filing (treatment) to identify the effect of severe identity theft on credit bureau characteristics. Since all individuals in this sample file an extended alert at some point in time, we avoid the selection-on-unobservables issue because the individuals in our sample are similarly motivated to file an alert once they have discovered evidence of fraud. Simply stated, we use the plausibly exogenous timing of fraud to compare the outcomes of already victimized extended alert filers with the outcomes of not-yet-victimized extended alert filers.

In addition, we focus our attention on extended alert filers because these individuals are required to submit a police report or an Identity Theft Report to file the alert and they may face penalties for falsifying this information (see Section 3.2 for more details). Thus, these consumers are very likely to be ID theft victims and focusing on them will allow us to identify the effects of ID theft on consumer credit outcomes and remove other potential reasons for filing another type of alert (e.g., precaution or worry).

We also use the NCVS data to show that extended alert filers represent the best proxy for our identity theft victim group of interest: consumers who experienced severe identity theft. Most victims of identity theft or fraud do not file a fraud alert with a credit bureau.[10] However, victims of severe identity theft — defined as those who experienced an identity theft incident that involved the opening of new accounts or the misuse of their personal information — are nine times more likely to file an extended fraud alert compared with other identity theft victims. Additionally, extended alert filers are six times more likely to be victims of severe identity theft (42 percent) compared with identity theft victims who did not file any fraud alert (7 percent).

Our analysis of the NCVS data also shows that extended alert filers closely resemble severe identity theft victims in the incidence and magnitude of OOP losses related to the theft. About a quarter of extended alert filers and victims of severe identity theft tend to have OOP losses, while only 13 percent of all identity theft victims have OOP losses. Moreover, extended alert filers and severe identity theft victims tend to have comparable average ($6,517 and $8,907, respectively) and median OOP losses ($330 and $280, respectively), which are larger than the average and median OOP losses of all victims of identity theft ($2,577 and $100, respectively). We combine data collected for three different waves of the

[10] According to Harrell (2019), the NCVS identifies about 8 percent of all identity theft victims as those contacting a credit bureau following identity theft. Among consumers suffering from more severe forms of identity theft, such as opening new accounts in the consumer's name, a much higher percentage (about 33 percent) of victims contact a credit bureau, and about one-third of those provide a police report to the credit bureau.

NCVS (2012, 2014, and 2016) to compare demographic characteristics of different types of identity theft victims and extended fraud alert filers (Table 2). This table shows that extended alert filers look more similar to severe identity victims than all victims in many demographic characteristics as well (e.g., share non-Hispanic White, share with income <$50,000). Based on these results, we argue that extended fraud alert filers are very likely to be severe identity theft victims and use terms *extended alert filers* and *severe identity theft victims* interchangeably.[11]

The evidence from the NCVS, together with the institutional details we described earlier, gives us confidence about the external validity of our results for the population of severe identity theft victims. This population is also particularly interesting as it includes individuals who are (1) economically vulnerable (e.g., individuals who have low incomes, who are non-White, and who have lower labor market attachment), (2) are exposed to the negative results of identity theft (large OOP losses, physical and mental health issues, time and effort costs to resolve fraud), and (3) unprepared to deal with its consequences.[12] In addition, most fraudulent transactions in the United States are subject to the so-called zero liability principle, such that most consumers will not experience direct monetary costs due to identity theft. Focusing on consumers who experience severe outcomes is therefore informative for policies that might be necessary to remediate negative financial outcomes for particularly vulnerable consumers. This feature of our study is similar to other recent studies that focus on vulnerable populations such as individuals who file for bankruptcy (e.g., Dobbie et al., 2020) or consumers who were victims of uncommon events like the Madoff scheme (Gurun, Stoffman, and Yonker, 2018).

Finally, we also argue that neither potential endogenous timing of filing nor reverse causality represent significant threats to causal inference for the consumers in our study. We discuss each of these possible identification challenges in the following subsections.

5.1.1 Exogeneity of Extended Alert Timing

One potential concern about our identification strategy is that the timing of the extended fraud alert may not be exogenous. Based on available evidence that identity theft is a crime of opportunity more than targeting, and our examination of patterns in aggregate alert filings in our data (e.g., the monthly frequency of new extended fraud alerts, as plotted in Figure 1), we believe the timing of identity theft

[11] Using the NCVS, we also find that extended alert filers represent a reasonable proxy for severe identity theft victims regardless of the method of definition of severe identity theft; extended alert filers track severe identity theft victims both in terms of prevalence and severity of identity theft.

[12] Total OOP losses reported in the NCVS include the amount lost by a victim not compensated by a lender, insurance, or another provider; and indirect costs associated with the crime (late fees, overdraft and bounced check fees, legal fees, and miscellaneous expenses incurred dealing with the event). With respect to time to resolve issues, 55 percent of extended alert filers take more than a week to resolve problems related to identity theft, versus 25 percent for identity theft victims who did not file an extended alert.

itself to be exogenous at the consumer level. But it is possible that individuals may not discover identity theft for a long time, allowing for incidents to accumulate before filing an alert. There may also be an endogenous lag between discovering identity theft and filing an alert, where some consumers have more unobservable motivation to act faster than others. This could result in better credit outcomes for individuals who file more quickly relative to those who file less quickly. Both an accumulation of fraud over time and an endogenous lag in alert filing would violate our assumption that extended alert filing is a good proxy for victimization.

Evidence from the NCVS does not support either of these hypotheses. Panel A of Figure A1 shows that, for extended alert filers, more than 82.7 percent of respondents report discovering identity theft within a quarter. Extended alert filers also manage to clear up their credit and financial problems within the same time frame as discovery (Figure A1, panel B). Similar to discovery timing, 85.2 percent of extended alert filers report clearing up all financial problems because of identity theft within one quarter. The pattern of reasonably fast fraud detection and resolution holds whether we consider all identity theft victims or extended alert filers in the NCVS, although extended alert filers take longer to discover fraud and take longer to clean up their finances (consistently with experiencing more severe identity theft). Taken together, these results show that extended alert filers discover fraud and take corrective actions quickly.

Nevertheless, to control for other potential time-invariant, unobservable factors that may be correlated with consumer credit outcomes, we estimate all our models with individual fixed effects. By adding individual fixed effects, we also control for individual-specific, time-invariant factors that may be correlated with the timing of victimization or their response to it.

5.1.2 Reverse Causality

One potential challenge to our identification strategy is reverse causality. Instead of consumers correcting credit reports in response to identity theft, some consumers may set out to clean their credit files in preparation for a mortgage or other major credit application. During this process, consumers may discover negative episodes in their reports — such as fraud — because they are actively applying for credit and paying more attention to their reports. This hypothesis implies that such consumers are likely to have indicators of fraudulent activity (e.g., address change reversals, new accounts that are closed immediately, and increases in delinquent accounts) in their files at *any* time before they file an extended fraud alert.

Our results summarized in Figure 2 — discussed in more detail in the following section — do not support the hypothesis that consumers who file extended fraud alerts are simply engaged in credit file repair before a major credit application or some other event. In particular, panels A, C, and D in Figure 2 show that activity indicative of severe identity theft is tightly concentrated just before the alert filing or at the time of filing and not distributed across the quarters prior to alert filing. Survey evidence from the NCVS also supports our conclusion that individuals who experience identity theft were not typically in the process of shopping for credit, with approximately only 1 percent of respondents who were victims of identity theft stating that they discovered misuse upon applying for credit, bank accounts, or loans. This finding is consistent for victims of severe identity theft and for extended alert filers as well.

5.2 Econometric Methodology

In our main analysis, we estimate the following event-study regression model for extended alert filers in the CCP:

$$Y_{it} = \beta_0 + \sum_{e=-8}^{22} \beta_{1e} T_e + \delta_i + X_{it}\gamma + \varepsilon_{it}, \quad (1)$$

where Y is an outcome variable of interest, and T is a set of event time dummy variables relative to the time of extended fraud alert filing. For example, T_{2i} is equal to 1 when two quarters have passed since alert filing and 0 otherwise. This approach measures the changes in the outcome variables up to eight quarters before fraud alert filing (to observe preexisting trends, if any), at the time of the filing, and up to 22 quarters after alert filing. These are all relative to the omitted period, which is quarters 22 to 9 before the alert filing. The vector of individual-level controls X_{it} includes a fifth-order polynomial in age, state fixed effects, calendar time fixed effects, and the interactions of state and calendar time fixed effects. We also include individual fixed effects, δ_i.[13] Standard errors are clustered at the individual level. As the sample used in these regressions includes only extended fraud alert filers, the only source of variation exploited is the variation in the time of victimization and fraud alert filing. This specification is standard in the literature and is used by Gallagher (2014); Gross, Notowidigdo, and Wang (2020); and Dobkin et al. (2018).

6. The Effects of Severe Identity Theft on Consumer Credit Characteristics

In this section, we use the econometric strategy described in Section 5 to examine three research questions. First, we examine what happens to severe identity theft victims when they experience fraud. Second, we explore their credit performance after severe identity theft (including any cleanup of fraudulent information from credit records). Third, we document long-term effects of severe identity theft on credit performance, borrowing and use of credit, loan default, and other consumer interactions with the

[13] Note that we cannot include fixed effects for the cohort of fraud alert filing in this specification because they would be perfectly collinear with individual fixed effects. As a robustness test (not shown), we included cohort fixed effects and zip code fixed effects, but omitted individual fixed effects, and obtained nearly identical results.

credit markets. We summarize our results for these three lines of inquiry in Figures 2–7. All figures report coefficients from the distributed lag regression model specified in Equation (1) for a number of outcome measures. The coefficients show the difference in the outcome variables between already victimized consumers and not-yet-victimized individuals over the time before and after identity theft. In addition to point estimates displayed as dots, all figures provide 95 percent confidence intervals as vertical bands. In the following subsections, we discuss our results for all consumers and for some consumers with more pronounced effects.

6.1 Evidence of Severe Identity Theft

We document changes in four credit variables that can be affected by severe identity theft and fraud in Figure 2. These variables include credit applications, number of new revolving accounts, reverse address changes, and Risk Scores. We show the effects of severe identity theft on these outcomes in the four panels of Figure 2 and discuss them in detail in the following paragraphs.

Panel A of Figure 2 displays a very large and transitory increase in the number of credit applications that coincides with the quarter the extended alert is filed. Relative to the base period (quarters 22 to 9 before alert filing), the average number of inquiries increases from 0.4 in the quarter before alert filing to 0.6 at the time of filing. The coefficient can be interpreted as six out of 10 consumers accumulating one additional credit application shortly before the fraud occurs. This increase is consistent with consumers' personal information being stolen by criminals and used to apply for credit. It is possible that consumers become aware of identity theft because this spike in applications triggers letters or phone calls from creditors. Results from the NCVS show that almost 50 percent of identity theft victims discover identity theft through such communications. The number of inquiries decreases to prefraud level by the third quarter after alert filing and remains on a downward trend.

Panel B of Figure 2 plots the average number of new revolving accounts for fraud victims before and after severe identity theft (revolving accounts include general-purpose credit cards issued by banks and credit unions as well as revolving credit offered by retailers for purchases made at their stores). This figure shows that new revolving accounts begin to increase sharply a few quarters before the extended alert filing and peak one quarter before filing. On average, one out of 10 severe identity theft victims have one new revolving account opened during that time. This finding is consistent with criminals using consumers' stolen personal information to open new revolving accounts. Extended alert filers have, on average, between 0.05 and 0.1 fewer new revolving accounts in the quarter after severe identity theft. The number of new accounts declines quickly once the fraud is discovered and the extended fraud alert filed. It remains suppressed for up to 22 quarters after fraud.

Certain types of serious identity theft and subsequent fraud involve criminals changing the address on the consumer's financial accounts, which can trigger a change in the address that creditors report to the credit bureau.[14] In our data, we are unable to distinguish between fraudulent and genuine address changes. However, we can see if an address change is reversed to the original address in the subsequent quarter. Thus, we can compare the pattern of *reverse address changes* at the time an extended fraud alert is filed with patterns prior to and after the event.[15] Panel C of Figure 2 plots the fraction of severe identity theft victims who revert their address to the prior quarter's address over event time. The coefficients imply that around 1 percent of victims reverse address changes at the time of fraud and an additional 1.5 percent of victims do the same one quarter after alert filing. Thus, we find evidence of a sharp increase in reverse address changes at the time the extended alert is filed and one quarter after, consistent with the consumer reversing address changes made by criminals.

Finally, panel D of Figure 2 shows a transitory decline in Risk Score of about 4 points shortly before the fraud alert filing and a subsequent recovery in the quarters after filing. However, the average increase in Scores that follows is typically larger than the transitory decline. On average, Risk Scores increase by about 10 points relative to the omitted period at the time of the fraud alert; we will revisit this finding in the next subsection.

The increases in inquiries, reverse address changes, and number of new revolving accounts near the time of the fraud alert filing, as well as the decline in Risk Score shortly before the placement of the extended fraud alert, provide convincing evidence that severe identity theft occurred within a reasonable time before the extended fraud alert was filed, if not exactly in the same quarter in which the alert was filed.

6.2 Persistent Changes in Credit Performance After Severe Identity Theft

In addition to the previously discussed indicators of severe identity theft in quarters just before and at the time of extended alert filing, panels A, B, and D of Figure 2 allow us to observe differences in the credit outcomes of severe identity theft victims in the medium to long term, up to five years following extended alert filing. In particular, these panels show the number of credit inquiries, the number of new revolving accounts, and Risk Score for up to 22 quarters after fraud occurrence. While panel D of Figure 2 shows that, on average, victimized consumers' Risk Scores are at least 10 points or higher even five years after severe identity theft, these consumers do not apply for credit as much as they did before the fraud, and

[14] Criminals may change addresses when taking over existing accounts, or they may apply for new accounts using the consumer's name but a different address.

[15] Recall that consumer address changes may be reversed in the credit bureau file after the discovery of fraud, but the history of address changes in the CCP is not updated and, therefore, is not affected by the reversal.

they have, on average, 0.2 *fewer* credit inquiries per quarter in this period (Figure 2, panel A). Consistent with this reduced number of inquiries, the number of new revolving accounts is about 0.12 lower for severe identity theft victims five years out (panel B). These results also indicate that the persistent improvement in Risk Score after severe identity theft may be explained in part by reductions in the number of inquiries and the number of new revolving accounts after fraud. The reductions in both of these indicators of credit demand can positively affect Risk Scores.

To examine the reasons behind the persistent improved creditworthiness of severe identity theft victims, we consider measures of credit performance such as the proportion of balances in good standing, the incidence of third-party collections, and the incidence of major derogatory events. Figure 3 provides evidence on the performance of severe identity theft victims with credit products several years after fraud. Panel A of Figure 3 shows that consumers keep a higher proportion of their card balances in good standing up to five years after severe identity theft. Fraud victims also maintain a lower incidence of major derogatory events on cards by about 4 percentage points (panel B) and a lower incidence of third-party collections by 6 to 7 percentage points (panel C). These three measures of credit performance capture different margins of adjustment in debt repayment behavior. Card balances in good standing (current) represent the strictest definition of performance (i.e., repaying debts on time without any delay). Major derogatory events on cards capture more serious delinquency such as charge offs, bankruptcies, and internal collections. Third-party collections are delinquent accounts placed for collection with external firms that specialize in recovering at least a portion of an outstanding debt that a consumer owes.

The sharp declines in the incidence of derogatory events and third-party collections at the time of an extended alert filing likely results from consumers disputing fraudulent accounts and other incorrect information in their credit reports. However, the persistence of these effects suggests that consumers changed their repayment habits to keep more credit accounts in good standing and out of collections as shown by the long-term effects of fraud on these variables.

To summarize our findings, we plot the share of the population with prime Scores (higher than 660) in our sample in panel D of Figure 3. Consistent with the decline in the average Risk Score before severe identity theft, shown in Figure 2, this figure shows that fraud activity at event time $e = -1$ lowers the share of prime consumers by 1.7 percentage points. However, after fraud, the share of prime consumers increases by 3.4 percentage points relative to the base period, which is a 5.1 percentage point increase relative to the quarter before fraud. This is an 11 percent increase over the sample average of 46 percent of prime consumers. The share of prime consumers continues to grow over time, and it is 7 percentage points higher after five years relative to the baseline period. This is a substantial change in both a statistical and economic sense.

It is important to note that the mechanical effect of credit file "cleaning" (i.e., removing fraudulent information from credit bureau files), while likely responsible for the initial gain in Risk Score immediately after the identity theft incident, is insufficient to explain the persistent positive changes in consumer behavior on *existing* credit accounts. The most plausible explanation for our results is that consumers paid little attention to their credit report information prior to suffering severe identity theft and began paying more attention after the incident. Several sources show that consumers do not pay close attention to their credit reports, credit scores, or other credit information. For example, according to a 2013 poll conducted by the National Foundation for Credit Counseling, 60 percent of adults 18 years or older had not checked their credit scores in the previous 12 months, and 65 percent had not reviewed their credit reports. Similarly, the Bureau of Justice Statistics found that only 42 percent of nonvictims reported that they had checked their credit reports in the past 12 months; this number was considerably higher, at 62 percent, among consumers who had experienced identity theft (Harrell, 2019).

Given the nature and potential economic effects of severe identity theft, it is likely that a fraud incident may increase the salience of credit information, increase the cost of acquiring/retaining credit, or encourage increased monitoring of credit reports and/or scores. Severe identity theft victims experience negative feelings (e.g., shock, anger, anxiety) that may be action inducing because of the seriousness of the event in a way that additional disclosures or reminders are not. Our calculations based on the NCVS data show that the number of identity theft victims who acknowledged checking their credit report increased by up to 15 percentage points upon victimization, and the number of victims who checked their bank or credit card statements increased by up to 26 percentage points.

Although we cannot directly test the inattention hypothesis with our data, our empirical results strongly suggest that a behavior change occurred after the fraud incident. In particular, the persistent changes we observe across multiple credit outcomes provide suggestive evidence of improved attention, which may have additional spillover effects on related factors such as financial literacy, after the severe identity theft incident. Most importantly, in Figure 3, we observe that individuals experience fewer major negative credit outcomes, such as accounts in collections or past due, in the quarters after severe identity theft. Our evidence that these measures are significantly and persistently lower throughout the postfraud period is consistent with consumers paying more attention to their credit information and possibly managing their accounts better. On the other hand, these results are inconsistent with the idea of a simple mechanical adjustment to credit outcomes because of a one-time removal of fraudulent information from consumers' credit files.

6.3 Which Consumers Improve Their Credit Performance?

Our previous results that show large increases in both the average Risk Score and in the share of consumers with prime Risk Scores in the years following severe identity theft have potentially far-reaching economic consequences, as they may allow borrowers to obtain more credit and at better terms. For example, on average, the annual percentage rate (APR) on a 30-year, fixed-rate mortgage decreases from 4.291 percent to 3.315 percent when a borrower moves from the 620–639 FICO score range to the 660–679 range.[16] Bracha and Meier (2015) show that moving from the 620–679 score range to the 680–739 range can decrease credit card interest rates by 3.5 percentage points (from 19.1 percent to 15.5 percent, on average). Thus, positive changes in the Risk Score may allow borrowers to save on financing expenses and have more access to credit to smooth negative income or expense shocks.

While any increase in credit scores may improve credit access and terms of credit, crossing into a higher score category is especially beneficial. While there are several thresholds in scores affecting creditworthiness, the most significant is the subprime–prime distinction, as documented extensively in the previous literature. To understand whether changes in consumer credit outcomes are more pronounced for consumers that cross into a higher score category, we apply our econometric strategy from Figure 3 to the subsample of extended alert filers who crossed the prime Risk Score threshold after severe identity theft. We define consumers as transitioning from the subprime to prime status if their Risk Scores are less than or equal to 660 in any of the four quarters before extended alert filing and are more than 660 at the time of alert filing or any of the four quarters after filing.

The changes in credit performance of the subprime-to-prime transition subgroup of our extended alert filer sample are presented in Figure 4. Comparing results in Figure 4 (subprime-to-prime transition group) to the results in Figures 2 and 3 (all borrowers), we can conclude that the subprime-to-prime transition group experiences improvements in credit performance that are three to five times the magnitude for all consumers. For example, the long-term increase in Risk Scores after severe identity theft was 10 points for all consumers. For the subprime-to-prime consumers, it is nearly 50 points in the year after severe identity theft and slowly declining to a relatively steady level of about 30 extra points compared with prefraud levels. In general, the subprime-to-prime transition group experiences considerably larger improvements in credit performance, although the magnitude of the increase is more likely to diminish over time. However, for all consumers, the improvements in performance are considerably lower but somewhat more persistent over time.

Next, we turn to an examination of the ways in which consumers use their improved creditworthiness in interactions with the credit markets following severe identity theft.

[16] This example is based on the national average mortgage interest rates provided by FICO on September 29, 2021.

6.4 Consumer Use of Improved Credit Standing After Severe Identity Theft

In this section, we consider how consumers use credit after severe identity theft and whether lenders alter the supply of credit to these individuals. While some identity theft victims appear to be more creditworthy after cleaning up their files (as we document in the previous sections), we examine if these consumers apply and receive more credit from lenders, which particular types of credit they receive, and how they perform on this additional debt. We show results for all severe identity theft victims in Figures 5–7; these figures depict the changes in the use of credit cards (Figure 5), auto loans (Figure 6), and mortgage loans (Figure 7). The comparable results for the subprime–prime transition group can be found in Appendix Figures A2–A4.

For credit card borrowing, the majority of changes to credit card accounts appears to occur in the first year following a fraud alert filing. In Figure 5, panel A shows that around 1 percent to 2 percent of consumers become new credit card holders in a few quarters preceding and following severe identity theft. We define a new cardholder as someone who transitions from having no cards in the previous quarter to having at least one card in the current quarter. It is important to note that the probability of becoming a new cardholder can increase because of identity theft or legitimate consumer activity.

Figure 5, panel B shows that more consumers reduce their total number of credit cards after initial increases in cards at the time of identity theft. On average, consumers have 0.2 fewer cards in the year after severe identity theft compared with their prefraud levels, which is a 10 percent decrease over the sample average of two cards per consumer. Total card balances (panel C) slightly reduce in the year following severe identity theft, then largely revert back to prefraud levels in subsequent years. Notably, total card limits (panel D) are persistently significantly lower even five years after fraud, mirroring the pattern in the number of cards in panel B and signifying — in combination with similar total balances relative to prefraud — that consumers are closing inactive accounts or not opening new ones. Some previous studies argue that card limits can capture the supply of unsecured credit, while card balances represent the demand for such credit (e.g., Gross and Souleles, 2002). Based on these definitions, both the supply of and demand for unsecured credit seem to contract in the year following identity theft, but card balances return nearly to prefraud levels shortly afterward.

We present the changes in automobile-related borrowing (auto loans) after severe identity theft in Figure 6. Panel A shows that around 0.5 percent to 1 percent of consumers in our sample become new auto loan holders (defined as switching from zero loans to a positive number of loans) in each of the three quarters following severe identity theft. This is a significant effect since, on average, only 2.2 percent of consumers become new auto loan holders per quarter in our sample (see Table 1). The average number of auto loans (panel B) decreases slightly in the couple of quarters following fraud, while auto loan balances (panel C) increase slightly, indicating that some consumers are opening new accounts, but others are using their increased creditworthiness to consolidate auto loans. Even with the new auto loans and balances, the share of auto balances in good standing (current or paid as agreed) increases significantly and remains elevated for many years following fraud (panel D).[17]

These results for auto loans are significant for a number of reasons. First, auto loans are used to finance purchases of automobiles, which are durable consumption goods. Thus, we find evidence that some severe identity theft victims — and especially those transitioning into the prime credit score bracket — use their improved creditworthiness to finance durable consumption. Second, we do not find evidence that consumers withdraw from the credit markets after severe identity theft. To the contrary, some consumers use their improved creditworthiness to borrow more and finance consumption. Third, despite additional debt, these consumers still perform considerably better on these new loans.

Next, we examine the use of mortgage credit after severe identity theft and summarize our results in Figure 7. Similar to the auto loan results, we find that a significant number of severe identity theft victims become new mortgage holders after identity theft (panel A). Around 0.5 percent to 1 percent of these consumers become new mortgage holders in each quarter postfraud. The number of mortgages (panel B) grows after identity theft to a cumulative effect of 0.1 additional mortgages by year five; these credit products have long maturities, so the cumulative effect on them may be larger than for other products that are designed to be repaid faster. Panel C shows that mortgage loan balances gently increase as a result of new mortgage activity relative to the pretheft levels, though our standard errors are quite large for this outcome variable. As with auto loans, the share of mortgage balances in good standing (panel D) increases slightly in the postfraud period, although the effect is not precisely estimated for quarters later in our sample.[18]

Overall, there is clear evidence of increased credit usage following the improvement in creditworthiness for victims of severe identity theft in the quarters and years following fraud, especially for the group of consumers who transition from being subprime to being prime credit risks. Despite

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[17] We show in the Appendix that the subprime-to-prime transition group is driving the new auto credit results. For this group, the average number of auto loans (Figure A3, panel B) increases by about 0.1 by the end of the second posttheft year, which is a 20 percent increase relative to the sample average. Auto loan balances (Figure A3, panel C) for the subprime-to-prime transition group also increase to around $3,500 relative to the pretheft levels, which is a 50 percent increase relative to the mean balances. Just as for the full sample of extended alert filers, even with this new credit, the share of auto balances in good standing (current or paid as agreed) increases significantly (Figure A3, panel D).

[18] As with auto loans, the effects are considerably more pronounced for the subprime-to-prime transition group, as depicted in Figure A4. The likelihood of being a new mortgage holder, the number of mortgages, mortgage balances, and performance on mortgage loans all increase steadily through our postfraud period; the differences relative to the comparison preperiod are consistently strongly statistically significant.

holding additional auto and mortgage loans and increased balances for these credit products, consumers continue to perform better (or, at least, no worse than before fraud) on these accounts for at least five years following severe identity theft. Interestingly, looking at panel A of each of the product charts (Figures 5–7), it appears that credit cards are the only product with significant increased activity prior to alert filing, which may include fraud, while auto loans or mortgages do not show such activity. This pattern is consistent with the industry insight that severe identity theft is more prevalent in credit cards than mortgages or auto loans.

7. Robustness Checks

7.1 Controlling for Long-Term Event Time Trends

As can be seen in Figure 4, panel D, some credit variables, such as Risk Score, may exhibit long-term trends in event time. These long-term trends may be explained by mean reversion in Risk Score and other variables. For example, positive changes in Risk Scores may attrite simply because the effects of credit information corrections or fraud removal decrease over time as they receive less weight in the contemporaneous Risk Score.

To separate the effect of mean reversion in credit variables from the longer-term effects of severe identity theft, we estimate the following parametric model adopted from Dobkin et al. (2018):

$$Y_{it} = \beta_0 + \beta_1 e + \beta_2 e^2 + \beta_3 1_{e\geq 0} + \beta_4 1_{e\geq 0} \times e + \beta_5 1_{e\geq 0} \times e^2 + \beta_6 1_{-4\leq e\leq -1} + \beta_7 1_{-4\leq e\leq -1} \times e + \delta_i + X_{it}\gamma + \varepsilon_{it}. \quad (2)$$

In this specification, e denotes fraud event time (from −22 to 22), $1_{e\geq 0}$ is an indicator variable equal to 1 for nonnegative event time, and $1_{-4\leq e\leq -1}$ is an indicator variable for the event time periods from $e = -4$ to $e = -1$. All other variables are as defined in Equation (1).

The specification in this model is motivated by the patterns in the data observed using the nonparametric specification in Equation (1). In particular, our earlier results show evidence of fraud shortly before alert filing and a discontinuous change in credit attributes at the time of extended alert filing. These two patterns motivate us to allow for discontinuous (intercept) shifts at the time of fraud ($e = -4$ to $e = -1$) and after fraud ($e \geq 0$). We also allow for a quadratic trend in event time. However, because this trend may shift after fraud, we interact the quadratic trend with the positive time indicator. Finally, we interact the linear component of the trend with the fraud time indicator.[19] While the

[19] Since there are only four periods for which the fraud time indicator is equal to 1, we do not interact it with the square of event time to avoid multicollinearity.

specification in Equation (2) does not allow for individual specific trends in event time, we relax this constraint in Section 7.4 and find very similar results.

Table 3 summarizes results for the 20 credit outcomes we estimated using Equation (2). The coefficients on the event time variables in this table reveal the presence of trends independent of the treatment (victimization) in some credit variables. Even after controlling for the long-run trends in these variables, we find effects of severe identity theft on credit attributes on impact, which are similar to our results in Figures 2–7. There is some attrition in these initial effects, as indicated by the interactions of time trends with the after-fraud indicator variable. For example, the coefficients on the interactions indicate that about 4 points of the initial jump in the Risk Score dissipate 11 quarters after the fraud event. Overall, these results are very similar to our main results obtained without controlling for long-term event time trends.

7.2 Balanced Panel

As we describe in detail in Section 4, our main data set is balanced in calendar time (all individuals are observed in every quarter between Q1:2008 and Q3:2013), but, by design, these data are not balanced in event time. This is because we include all consumers who file extended fraud alerts in this period and, thus, some of them will be observed for many quarters before alert filing (e.g., a 2013 filer), while others will have mostly postfiling history (e.g., a 2008 filer). One concern with this feature of the data is that we rely on different cohorts of filers to estimate treatment effects prefraud and postfraud. To address this concern, we expand our data set to include credit outcomes from Q1:2003 to Q1:2019 for all extended fraud alert filers that appear in the CCP and who filed their extended alerts between Q1:2008 and Q3:2013. With this expansion, every severe identity theft victim is linked with outcome data for up to 24 quarters before fraud and up to 22 quarters after fraud. In addition, we balance this panel in event time by removing all individuals who are not present in the data in event quarter -22 and 22 (people may have no data because they have not entered the CCP yet or they exited it because of death or migration). These restrictions reduce the sample to 42,799 individuals. We report results for this sample balanced in event time in Appendix Figures A5–A9. The results are largely comparable to our base results reported in Figures 2–7.

7.3 Heterogeneous Effects: Consumers Without Credit Inquiries Before Severe Identity Theft

To understand whether the effects of severe identity theft vary depending on the credit characteristics of the borrower, we study the effects of fraud on consumers without credit inquiries before and at the time of extended alert filing and compare these effects with the results for all consumers. Credit inquiries may capture two activities: (1) shopping for credit by consumers, and (2) shopping for credit by criminals using stolen consumer personal information. We hypothesize that consumers without inquiries may be (1) less attached to the credit market and less attentive to their credit information, or (2) subject to existing account fraud or other fraud that does not result in credit inquiries. Studying consumers without credit inquiries also allows us to test if our base results are affected by reverse causality, where some consumers may shop for credit, discover fraud, and then clean their credit bureau files (although, as we discussed previously, the NCVS indicates this is a rare occurrence).

Results for the estimation of Equation (1) for consumers without inquiries in the three quarters before and the quarter of extended alert filing can be found in Appendix Figures A10–A14. Even though we use data for Q1:2008–Q3:2013 in these figures, we rely on credit inquiries data in a few quarters before Q1:2008 and after Q3:2013 to assign consumers into this category. The decline in credit inquiries at the time of severe identity theft shown in panel A of Figure A10 is mechanical (we only include people without inquiries in this period), but the other results are not. Our results suggest that no-inquiry victims experience larger positive effects after victimization on credit performance indicators (e.g., incidence of derogatory events and third-party collections, share of card balances current, Risk Score). This finding might suggest that this subgroup of consumers exhibited more inattention before fraud than the severe identity theft victim population as a whole. The results for no-inquiry victims in Figures A12–A14 are broadly similar to the results for the whole population of extended alert filers. These consumers reduce their credit card activity but obtain more mortgage credit, increase auto loan balances, and keep more balances in good standing. These consumers also apply for credit after severe identity theft, as suggested by the number of inquiries in Figure A11. Overall, the findings for no-inquiry consumers suggest that these consumers are similar to other severe identity theft victims as they do not withdraw from credit markets and they use their improved creditworthiness to obtain new credit.

7.4 Controlling for Individual-Level Mean Reversion

As mentioned previously, the econometric model in Equation (2) assumes a common mean reversion for all individuals in both the pre- and postalert filing time periods. If there is substantial heterogeneity in mean reversion across individuals, imposing a common mean reversion across individuals may mask the true effect of severe identity theft on individuals. Because of the granular nature of our data, we have a long time series for each individual in our sample, which can allow for panels to have their own individual time trends.

To distinguish the effect of mean reversion from that of severe identity theft, we specify a model similar to that in Musto (2004):

$$Y_{it} = \beta_0 + \delta_i + \delta_i \times t + \delta_i \times t^2 + \beta_1 D_{it} + \alpha_t + \varepsilon_{it}, \tag{3}$$

where δ_i is an individual fixed effect to be estimated and $\delta_i \times t + \delta_i \times t^2$ is an individual-level quadratic time trend.[20] The variable of interest in this specification is D_{it}, an indicator variable equal to 1 when individual i has an extended fraud alert filed at time t. This variable captures the difference in a variable of interest between the times before and after severe identity theft. By specifying an individual quadratic time trend for each consumer, we can more precisely separate the effect of mean reversion from the effect of the extended fraud alert.

We present results of this analysis with the specification in Equation (3) for all our variables of interest in Appendix Table A1. In most cases, the estimates are quantitatively similar to those previously reported and highly statistically significant. After controlling for individual fixed effects and individual mean reversion, we find that severe identity theft victims gain 14 points in Risk Scores, experience 1 percent of reverse address changes, have more card balances in good standing, and have a lower incidence of third-party collection and major derogatory events postfraud. Reported R^2 is high because the estimated individual effects, along with the individual quadratic time trends, account for a significant portion of the variation in these credit variables.

8. Discussion and Conclusion

This paper uses a unique data set of anonymized U.S. credit bureau records, including details on extended fraud alert filings, to examine the effects of severe identity theft on Risk Scores, access to credit, and credit portfolios. We classify those individuals who place an extended fraud alert in their credit bureau files as the group of consumers that most closely proxy for victims of severe identity theft. We base our determination on an analysis of fraud alert and severe identity theft prevalence and consumer characteristics in our credit bureau data and in the NCVS, as well as extended alert filing procedures that strictly require fraud victims to file a police report or an Identity Theft Report (with accompanying evidence of identity theft and penalties for misrepresenting this information). Severe identity theft victims represent particularly interesting subjects for a study of consumer credit outcomes because such consumers are more vulnerable to identity theft, more likely to suffer as a result of identity theft, and less prepared to deal with the distressing consequences of identity theft. The nature of the extended fraud alert

[20] As mentioned in the previous sections, use of individual-level quadratic time trends is motivated by heterogeneity and nonlinearity in trends in credit outcomes observed in the data. Estimates using a linear time trend produce similar results.

filing system and our data — collected quarter by quarter, and thus reflecting fraud activity present in each quarter — provide us with unique advantages relative to other studies of consumer financial fraud.

Exploiting the exogenous nature of the timing of fraud victimization, we find evidence of severe identity theft shortly before extended alert filing, with average Risk Scores of fraud victims and increases in new (likely fraudulent) card accounts, inquiries, and instances of reverse address changes. The negative effects stemming directly from severe identity theft generally persist between one and two quarters. After these initial effects have passed, Risk Scores of severe identity theft victims rise by an average of 10 points, increasing the proportion of fraud victims with prime Risk Scores by 5 percentage points, or 11 percent. For many consumers, this effect is persistent over time and remains for as long as 20 quarters after fraud. We also find that victims have more card balances in good standing and a lower average incidence of derogatory events and third-party collections. The persistence of the reduction in the incidence of major derogatory and third-party collection events is particularly striking.

We also document that some severe identity theft victims take advantage of their improved financial standing to obtain additional credit. In particular, we find evidence that consumers obtain additional auto loans and mortgages after fraud and consolidate their use of credit cards while maintaining or improving their performance on existing card balances. We observe increases in the number of new loans, total loans, and balances for these individuals, with the increases particularly pronounced for the group of consumers who transition from having subprime to prime Risk Scores after fraud and gain the most ground in obtaining favorable credit terms. This finding is especially important because auto loans and mortgages are used to finance large durable consumption purchases or investment in real estate. Despite having additional loans and higher balances on those loans, this population manages their credit as well as or better than before severe identity theft by maintaining a larger fraction of balances in good standing.

Our empirical results provide robust evidence that allow us to evaluate the plausibility of a number of potential drivers for the identified effects of severe identity theft and the persistence of those effects. In particular, we argue that limited attention may play an important role in explaining the behavior of severe identity theft victims. The asymmetric positive impact on key credit variables upon fraud victimization, where credit performance improved by more after the event than it deteriorated before the event, suggests that consumers were not focused on their credit reports prior to victimization.

The persistent improvement over time to consumer credit attributes suggests at least two conclusions. First, consumers may be paying increased attention to their credit and credit reports for a substantial period after severe identity theft. Second, the fact that some consumers apply and obtain additional credit may imply that they take advantage of their better creditworthiness and do not shy away from credit markets. These are important findings to understand the financial impact of severe identity theft on the interactions of consumers with credit markets after serious fraud incidents.

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Table 1. Summary Statistics — Extended Alert Filer Sample

Variable	Obs.	Mean	Std. Dev.
Number of inquiries, past 3 months	1,039,906	1.0	1.6
Number revolving accounts opened within 6 months	1,109,464	0.3	0.7
Number of address reversals in the last quarter	1,210,927	0.011	0.106
Risk Score	1,190,342	649.0	117.5
Percent of bankcard balances in good standing (%)	684,747	94.8	19.4
Share w/major derogatory events on cards (%)	1,210,927	13.0	33.6
Share w/third-party collections (%)	1,210,927	24.9	43.2
Share prime consumers (Risk Score > 660) (%)	1,210,927	46.2	49.9
Share w/new bankcard(s) (%)	1,210,927	2.0	13.9
Number of bankcards	1,210,927	2.0	2.2
Total bankcard balance ($)	853,853	6,175	15,662
Total bankcard credit limit ($)	853,853	21,033	31,619
Share w/new auto loan(s) (%)	1,210,927	2.2	14.6
Number of auto loans	1,210,927	0.5	0.7
Total balance on auto loans ($)	1,210,927	6,878	12,902
Percent of auto loans in good standing (%)	484,684	84.6	35.0
Share w/new mortgage(s) (%)	1,210,927	1.3	11.5
Number of mortgage accounts	1,210,927	0.4	0.7
Total balance on mortgage loans ($)	379,784	239,473	275,197
Percent of mortgage loans in good standing (%)	342,501	99.1	7.5

Notes: Risk Score is the Equifax Risk Score. Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Table 2. Average Characteristics of Identity Theft Victims and Extended Alert Filers (NCVS Data)

	(1) ID Theft Victim	(2) Severe ID Theft Victim	(3) Filed Extended Fraud Alert
Share high school diploma or less (%)	23	33	19
Share bachelor's degree or higher (%)	46	34	46
Average age	47	46	46
Share non-Hispanic White (%)	75	61	66
Share married (%)	59	48	56
Share female (%)	52	54	53
Share own home (%)	71	61	65
Share income <$50,000 (%)	27	42	32
N	19,427	1,746	315

Notes: Authors' calculations using pooled data from the 2012, 2014, and 2016 National Crime Victimization Survey's (NCVS) Identity Theft Supplements. All calculations made using sample weights.

Table 3. The Effect of Severe Identity Theft on Credit Variables After Controlling for Event Time Trends

Variables	(1) Risk Score	(2) Inquiries	(3) Address Reversals	(4) Revolving Accounts Within 6 Months	(5) Per. Card Bal. Good Standing	(6) Derogatory Events	(7) Collections
Time	0.964	-0.189	-0.128	-0.000121	-0.00521	-0.00443	0.00402
	(3.289)	(0.201)	(0.151)	(0.000)	(.)	(0.043)	(0.043)
Time2	0.00470	0.0000339	0.0000761	-0.000000789	0.0000241	-0.000196***	0.0000414
	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1(Time≥0)	11.01***	0.325***	0.0138	0.0113***	0.0122***	-0.00414	-0.0793***
	(0.932)	(0.023)	(0.012)	(0.001)	(0.004)	(0.006)	(0.006)
1(Time≥0)×Time	-0.357*	-0.0925***	-0.0208***	-0.00189***	0.000744	0.00590***	0.00184
	(0.195)	(0.004)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
1(Time≥0)×Time2	0.00827	0.00304***	0.000491***	0.0000756***	-0.0000615*	0.000178***	-0.000205***
	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1(−4≤Time≤−1)	-5.100***	0.359***	0.102***	0.00456***	-0.00968**	0.0329***	-0.0147**
	(0.921)	(0.025)	(0.012)	(0.001)	(0.004)	(0.006)	(0.006)
1(−4≤Time≤−1)×Time	-1.345***	0.0915***	0.0243***	0.000955***	-0.00280***	0.00744***	-0.00286**
	(0.185)	(0.005)	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)
Constant	394.3	-33.58	-23.51	0.0490	0.0464	1.668	-0.524
	(653.606)	(37.950)	(29.686)	(0.099)	(.)	(8.200)	(8.243)
R-squared	0.0411	0.0236	0.0186	0.00392	0.00479	0.0146	0.00683
Observations	1,190,292	1,039,906	1,109,429	1,210,858	684,738	1,210,858	1,210,858

Notes: This table shows the effect of severe identity theft on credit outcomes indicated in the first row modeled using Equation (4). This model allows for a quadratic trend in event time (Time). This feature is designed to remove mean reversion in credit attributes. This model also allows for changes in trend at the time of fraud (−4 to −1) and after fraud (Time≥0). The model includes individual fixed effects and calendar time fixed effects. The results indicate that there are negative changes in credit variables at fraud time and positive changes after fraud. Standard errors are clustered at the individual level and reported in parentheses. Risk Score is the Equifax Risk Score.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Table 3. The Effect of Severe Identity Theft on Credit Variables After Controlling for Event Time Trends (continued)

Variables	(8) Prime Indicator	(9) New Bankcard	(10) Number of Cards	(11) Cards Balance	(12) Cards Limit	(13) New Auto	(14) Number of Auto
Time	-0.00234	0.0000716	-0.109	749.6	2280.5	-0.0000364	0.0340
	(0.043)	(0.000)	(0.115)	(.)	(512277.902)	(0.000)	(0.052)
Time2	0.0000175	-2.63e-08	-0.0000931	-0.0735	-3.257	-0.00000813	0.0000777
	(0.000)	(0.000)	(0.000)	(1.734)	(2.670)	(0.000)	(0.000)
1(Time≥0)	0.0333***	0.00853***	-0.0906***	-448.4**	-1281.4***	0.00941***	-0.0357***
	(0.004)	(0.002)	(0.019)	(206.791)	(293.471)	(0.002)	(0.008)
1(Time≥0)×Time	0.00240***	-0.00229***	-0.0106**	50.73	27.25	-0.00132***	-0.000364
	(0.001)	(0.000)	(0.004)	(43.720)	(66.221)	(0.000)	(0.002)
1(Time≥0)×Time2	-0.0000858**	0.0000914***	0.000219	-1.713	4.507	0.0000554***	-0.000194***
	(0.000)	(0.000)	(0.000)	(1.834)	(2.828)	(0.000)	(0.000)
1(−4≤Time≤−1)	-0.0253***	0.00878***	0.0877***	95.11	34.99	0.00244	-0.0175**
	(0.004)	(0.002)	(0.019)	(211.286)	(294.276)	(0.002)	(0.008)
1(−4≤Time≤−1)×Time	-0.00640***	0.00194***	0.0193***	26.78	0.191	0.000575	-0.00346**
	(0.001)	(0.000)	(0.004)	(43.238)	(59.450)	(0.000)	(0.002)
Constant	-1.467	0.528*	-18.20	164099.9	473514.7	-0.339**	1.408
	(8.220)	(0.293)	(22.984)	(.)	(1.397e+08)	(0.146)	(9.655)
R-squared	0.0113	0.00283	0.0638	0.00602	0.0354	0.00199	0.00571
Observations	1,210,858	1,210,858	1,210,858	853,825	853,825	1,210,858	1,210,858

Notes: This table shows the effect of severe identity theft on credit outcomes indicated in the first row modeled using Equation (4). This model allows for a quadratic trend in event time (Time). This feature is designed to remove mean reversion in credit attributes. This model also allows for changes in trend at the time of fraud (−4 to −1) and after fraud (Time≥0). This model includes individual fixed effects and calendar time fixed effects. The results indicate that there are negative changes in credit variables at fraud time and positive changes after fraud. Standard errors are clustered at the individual level and reported in parentheses. Risk Score is the Equifax Risk Score.

Sources: Authors’ calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Table 3. The Effect of Severe Identity Theft on Credit Variables After Controlling for Event Time Trends (continued)

Variables	(15) Total Auto Balance	(16) Perc. Auto Bal. Current	(17) New Mortgage	(18) Number of Mortgages	(19) Total Mortgage Balance	(20) Perc. Mort. Bal. Current
Time	1450.0	0.0136	0.000118	0.000128	-1389.1	0.000817*
	(1221.962)	(0.011)	(0.000)	(0.001)	(880.136)	(0.000)
Time^2	1.681	0.000180***	0.00000805	0.000115**	20.38	0.0000259
	(1.265)	(0.000)	(0.000)	(0.000)	(34.379)	(0.000)
1(Time≥0)	-191.9	0.0172***	0.00465***	-0.0148***	-291.1	-0.00111
	(147.657)	(0.007)	(0.001)	(0.006)	(3340.204)	(0.002)
1(Time≥0)×Time	23.57	-0.00615***	-0.000523**	0.00436***	106.6	-0.000854*
	(32.487)	(0.001)	(0.000)	(0.001)	(777.092)	(0.000)
1(Time≥0)×Time^2	-6.262***	-0.000199***	0.00000309	-0.000288***	-28.17	-0.0000240
	(1.403)	(0.000)	(0.000)	(0.000)	(35.276)	(0.000)
1(−4≤Time≤−1)	-162.2	0.00165	0.000343	-0.00378	-140.9	-0.00128
	(145.227)	(0.007)	(0.001)	(0.005)	(3288.030)	(0.002)
1(−4≤Time≤−1)×Time	-23.25	0.00113	0.0000667	-0.00158	-130.7	-0.000346
	(28.947)	(0.001)	(0.000)	(0.001)	(650.724)	(0.000)
Constant	206498.0	3.197	0.212	-0.771	-108347.8	0.794***
	(212943.075)	(1.956)	(0.243)	(0.905)	(615978.213)	(0.156)
R-squared	0.00638	0.0154	0.00207	0.0162	0.0151	0.00696
Observations	1,210,858	484,684	1,210,858	1,210,858	379,784	342,501

Notes: This table shows the effect of severe identity theft on credit outcomes indicated in the first row modeled using Equation (4). This model allows for a quadratic trend in event time (Time). This feature is designed to remove mean reversion in credit attributes. This model also allows for changes in trend at the time of fraud (−4 to −1) and after fraud (Time≥0). This model includes individual fixed effects and calendar time fixed effects. The results indicate that there are negative changes in credit variables at fraud time and positive changes after fraud. Standard errors are clustered at the individual level and reported in parentheses. Risk Score is the Equifax Risk Score.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure 1. Number of Extended Alert Filers over Time

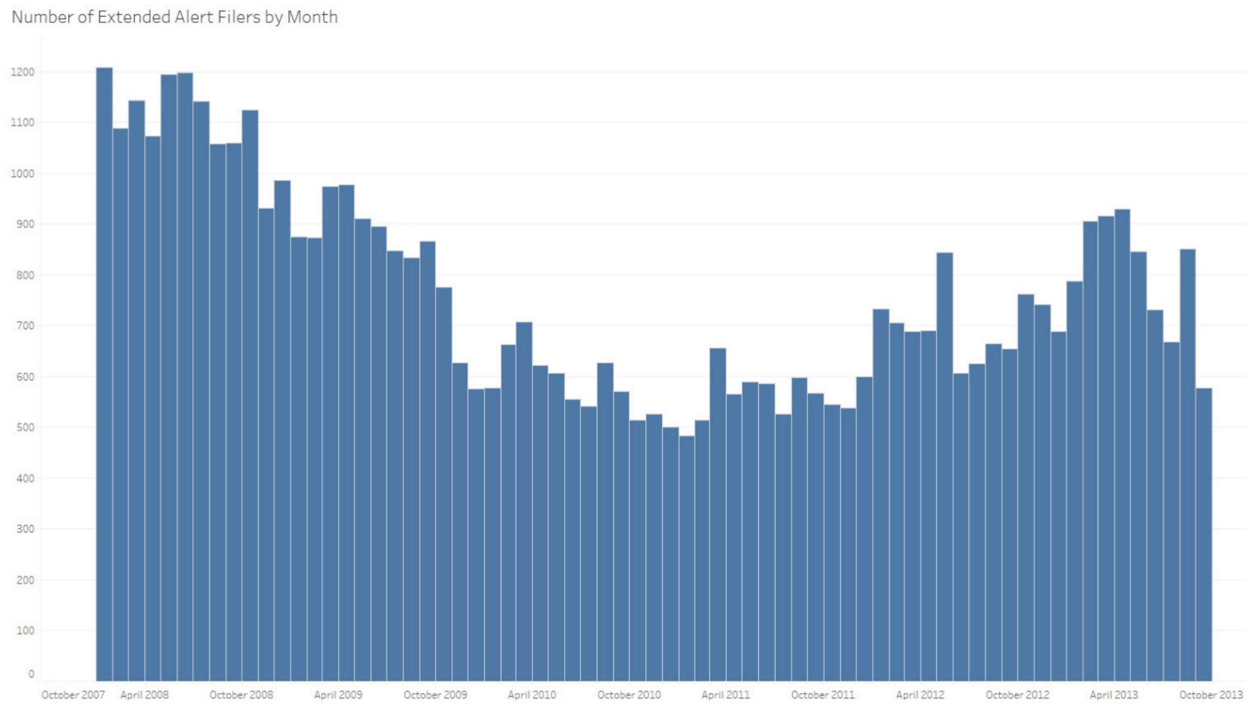
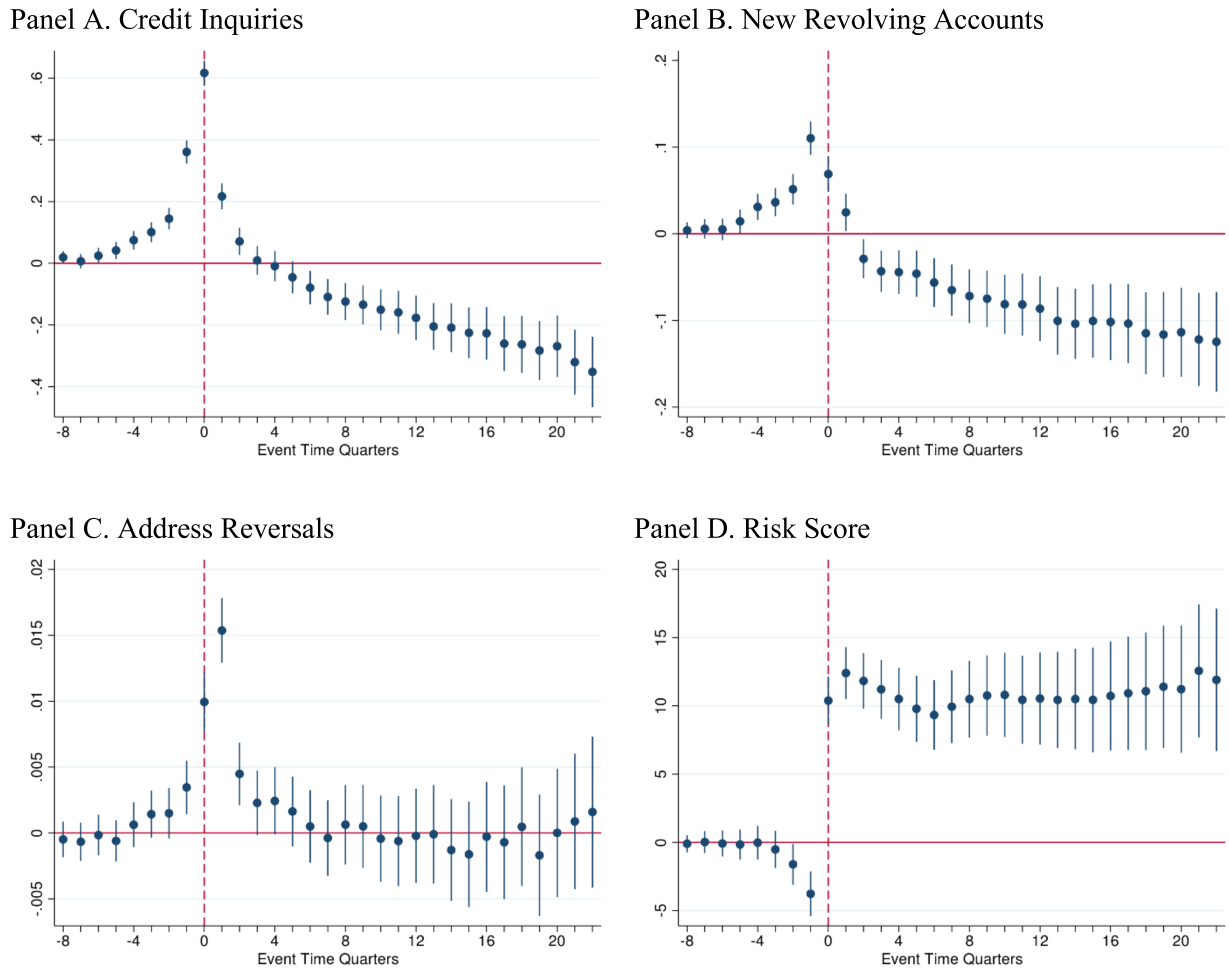
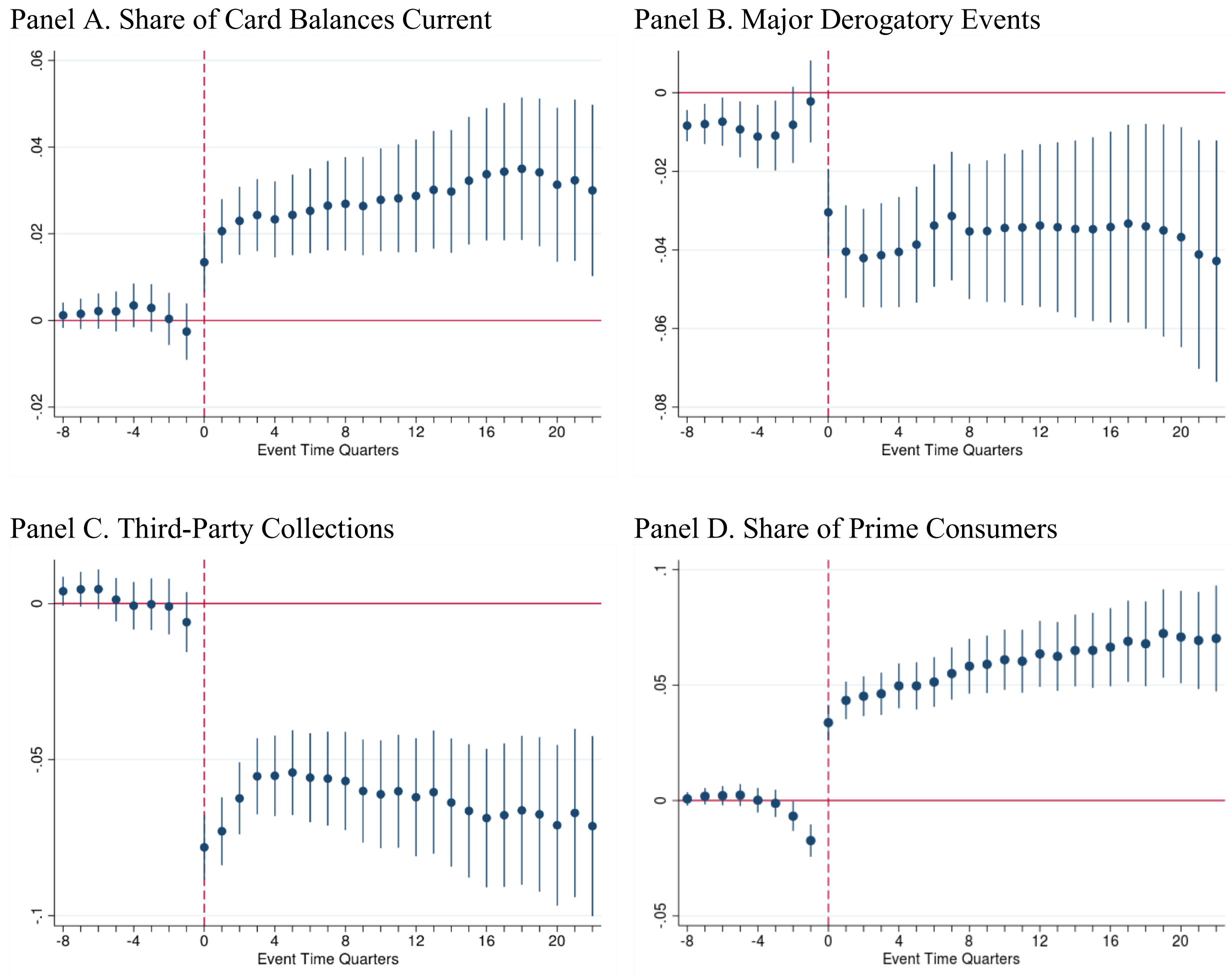


Figure 2. Indicators of Potential Severe Identity Theft



Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013. Risk Score is the Equifax Risk Score.

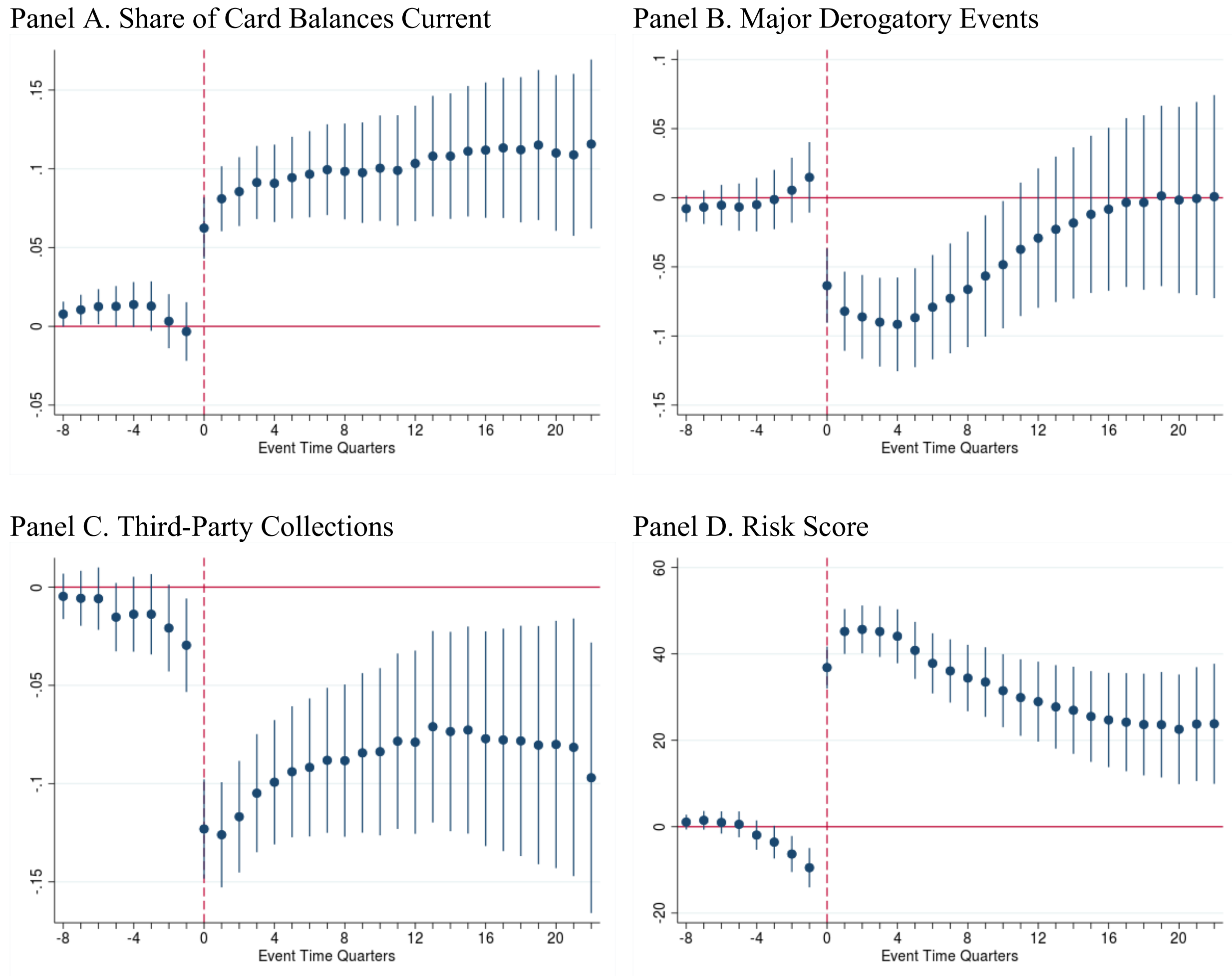
Figure 3. Credit Performance Before and After Severe Identity Theft



Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Prime is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

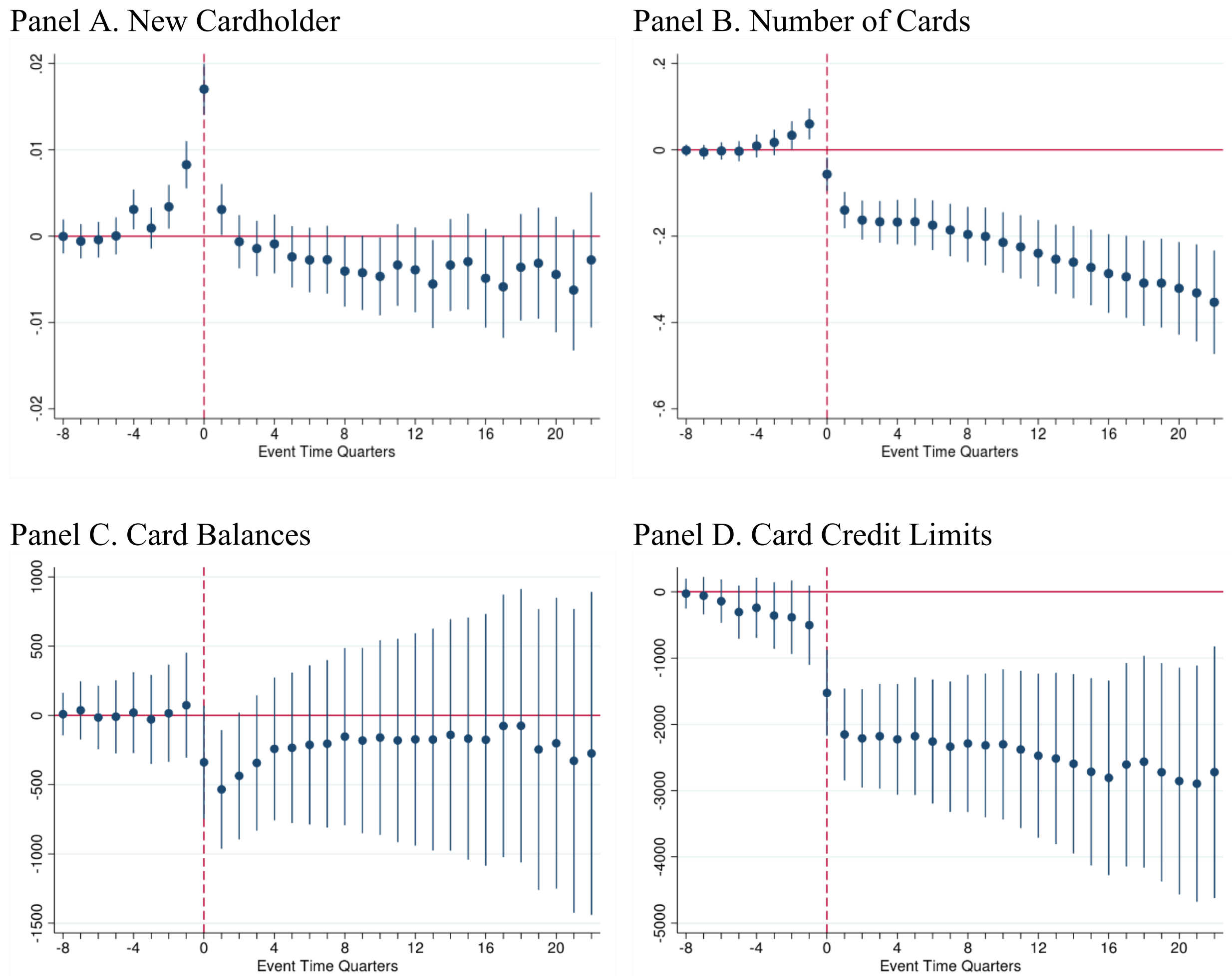
Figure 4. Credit Performance Before and After Severe Identity Theft — Subprime-to-Prime Transition Group



Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure 5. Credit Card Use After Severe Identity Theft Resolution

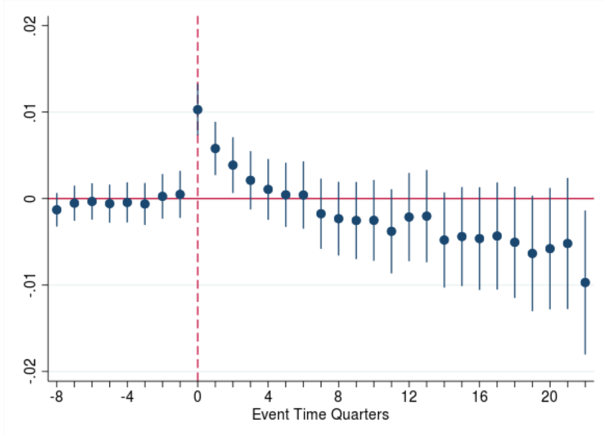


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

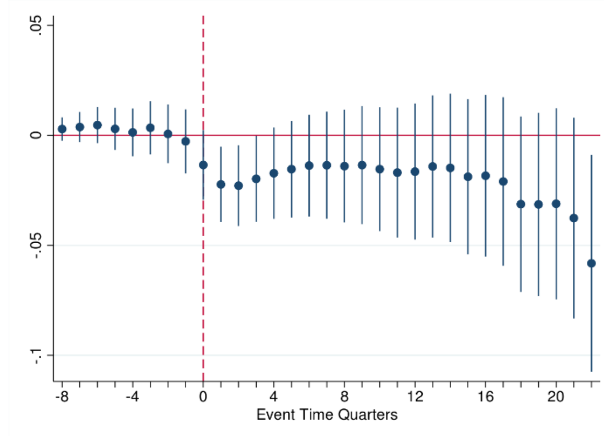
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure 6. Auto Loan Use After Severe Identity Theft Resolution

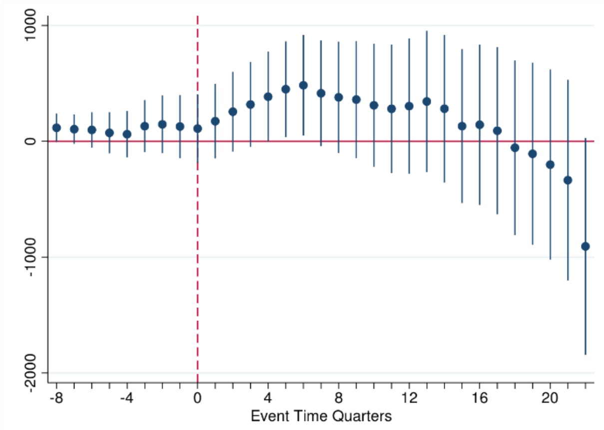
Panel A. New Auto Loan Holder



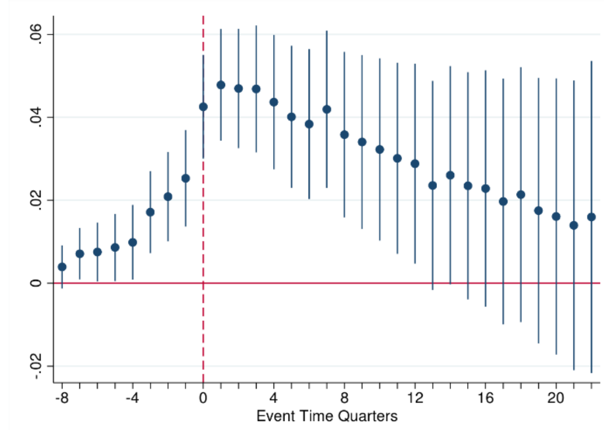
Panel B. Number of Auto Loans



Panel C. Auto Loan Balances



Panel D. Share of Auto Balances Current

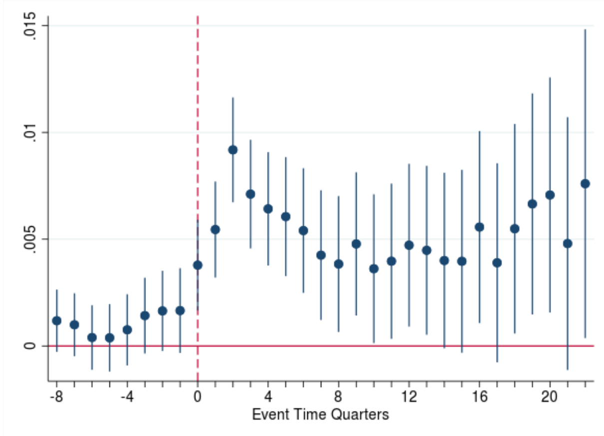


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

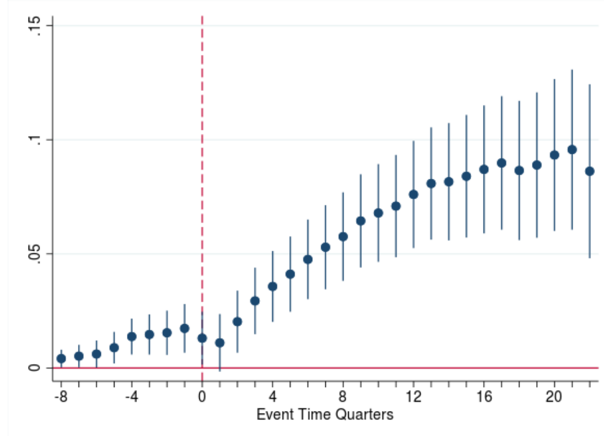
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure 7. Mortgage Loan Use After Severe Identity Theft Resolution

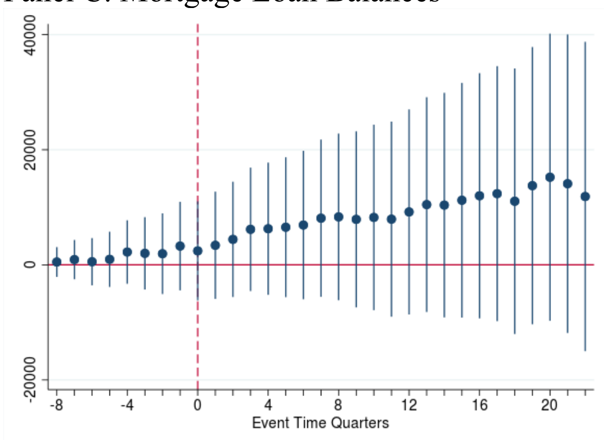
Panel A. New Mortgage Loan Holder



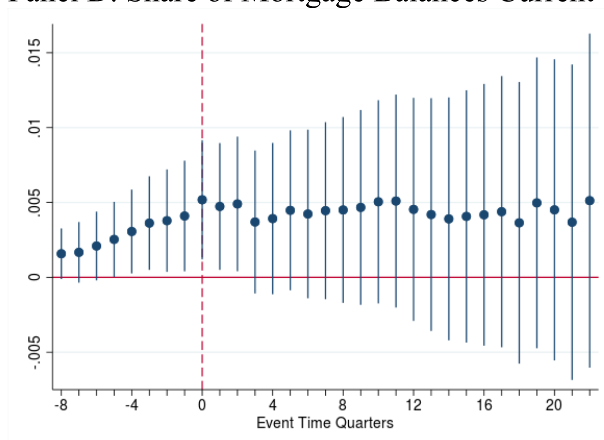
Panel B. Number of Mortgage Loans



Panel C. Mortgage Loan Balances



Panel D. Share of Mortgage Balances Current



Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Appendix

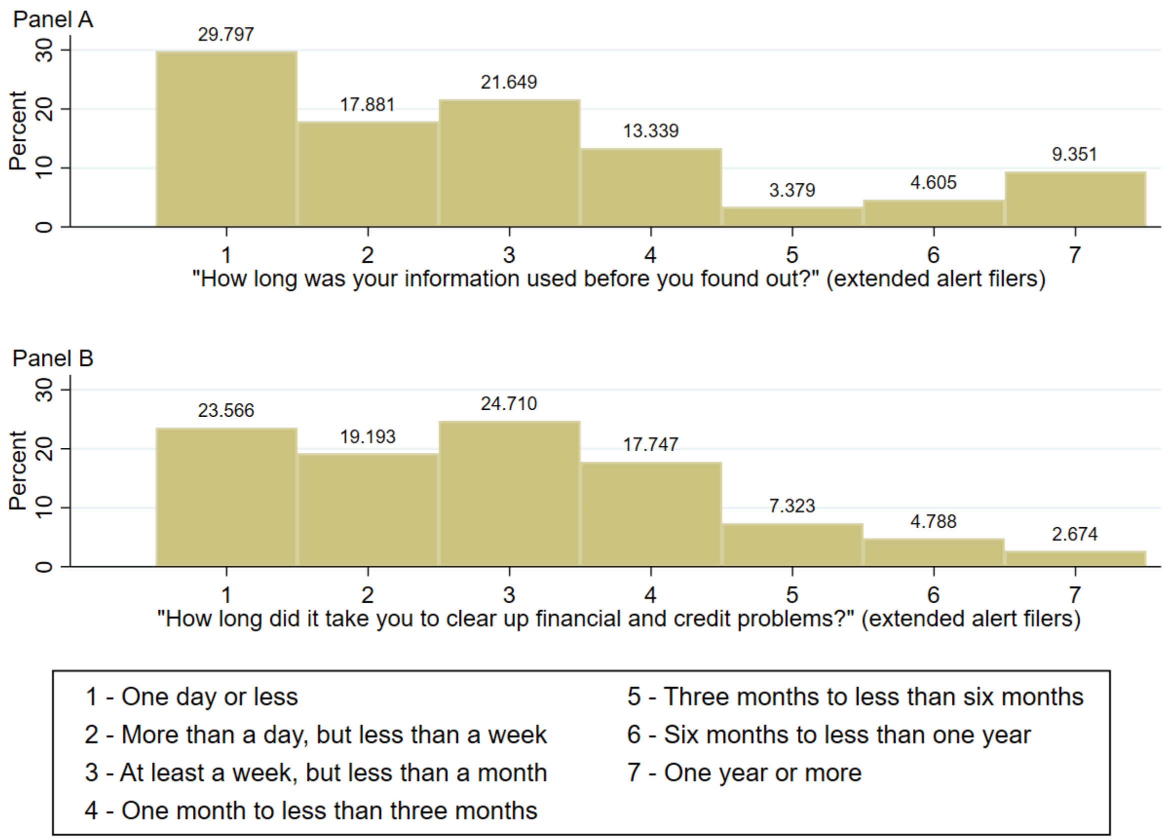
Table A1. The Effect of Severe Identity Theft on Credit Bureau Activity, Controlling for Individual Mean Reversion

Variable	After Alert Filed	Std. Errors	R^2	Obs.
Number of inquiries, past 3 months	0.0780***	(0.010)	0.433	1,039,817
Number revolving accounts opened, past 6 months	-0.0708***	(0.005)	0.421	1,109,248
Address reversals in last quarter	0.00929***	(0.001)	0.178	1,210,927
Risk Score	14.29***	(0.311)	0.929	1,190,323
Percent of nondelinquent bankcard balances †	0.0170***	(0.001)	0.649	682,749
Incidence of major derogatory events on bankcards	-0.0264***	(0.002)	0.713	1,210,927
Incidence of third-party collections	-0.0678***	(0.002)	0.632	1,210,927
Prime indicator (1 if Risk Score > 660)	0.0509***	(0.002)	0.876	1,210,927
New bankcard account indicator	0.00169**	(0.001)	0.143	1,210,927
Number of bankcards	-0.159***	(0.006)	0.94	1,210,927
Total bankcard balance †	-551.3***	(58.854)	0.833	852,772
Bankcard limit †	-1,674.2***	(94.224)	0.916	852,772
New auto loan indicator	0.00687***	(0.001)	0.125	1,210,927
Number of auto loans	-0.0260***	(0.002)	0.864	1,210,927
Total balance on auto loans	-163.9***	(48.592)	0.837	1,210,927
Percent of nondelinquent auto loan balances †	0.0229***	(0.002)	0.726	483,466
New mortgage indicator	0.00440***	(0.001)	0.145	1,210,927
Number of mortgage accounts	-0.0136***	(0.002)	0.931	1,210,927
Total mortgage balance †	-1,198.80	(998.625)	0.947	379,143
Percent of nondelinquent mortgage balances †	0.000727	(0.001)	0.579	341,678

Notes: All specifications include individual fixed effects, individual quadratic time trends, and time fixed effects. For variables marked with †, individual linear time trends are included instead of individual quadratic time trends to reduce multicollinearity. Standard errors are clustered at the individual level. Risk Score is the Equifax Risk Score. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

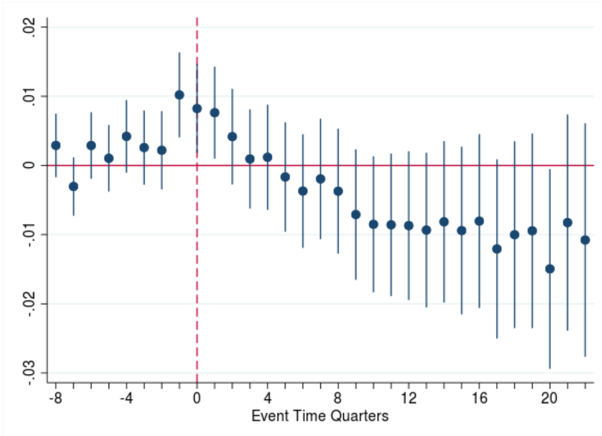
Figure A1. Speed of Discovery and Clearing Up Severe Identity Theft



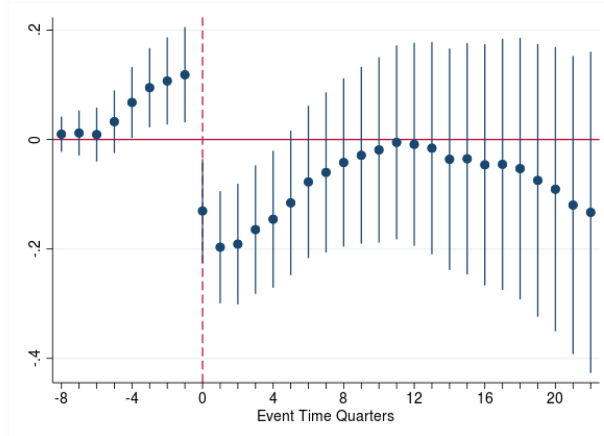
Notes: Survey responses from the Bureau of Justice Statistics' National Crime Victimization Survey 2012, 2014, and 2016 Identity Theft Supplements. Panel A: Percent of extended alert filers who discovered fraud less than three months after its occurrence is 82.7 percent. Panel B: Percent of extended alert filers reporting that clearing up financial and credit problems took less than three months is 85.2 percent.

Figure A2. Credit Card Use After Severe Identity Theft Resolution: Subprime-to-Prime Transition Group

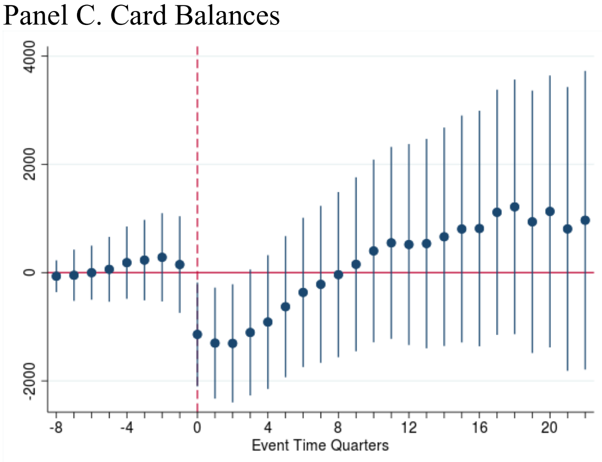
Panel A. New Cardholder



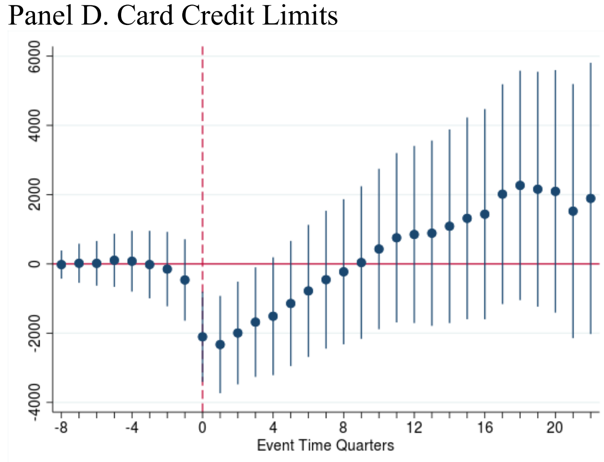
Panel B. Number of Cards



Panel C. Card Balances



Panel D. Card Credit Limits

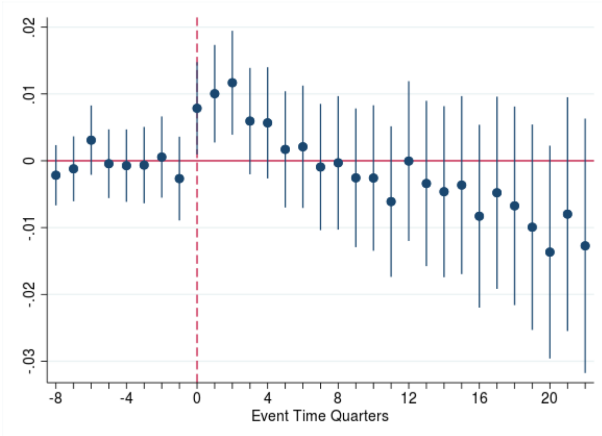


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. *Prime* is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

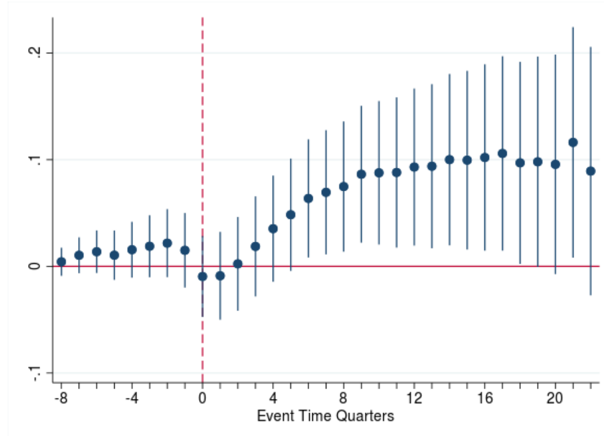
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A3. Auto Loan Use After Severe Identity Theft Resolution: Subprime-to-Prime Transition Group

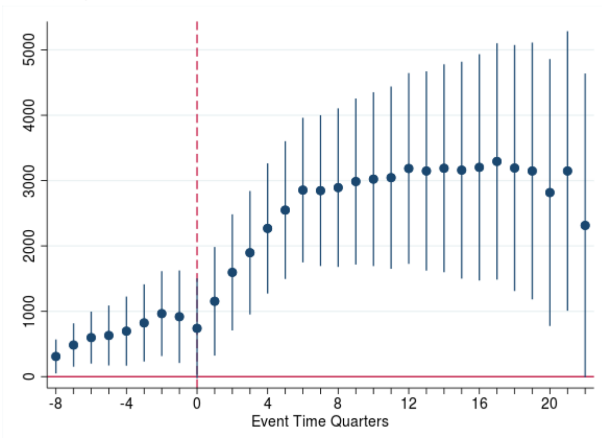
Panel A. New Auto Loan Holder



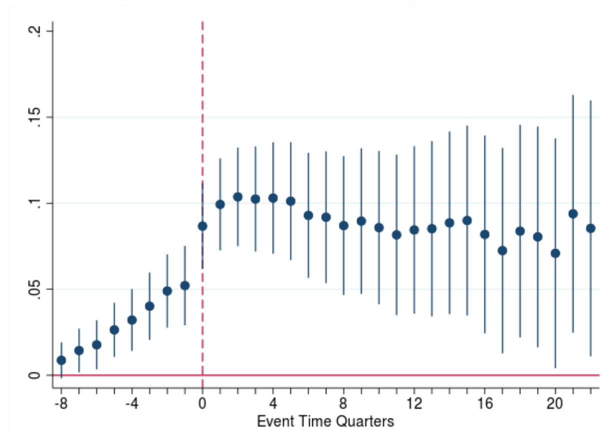
Panel B. Number of Auto Loans



Panel C. Auto Loan Balances



Panel D. Share of Auto Balances Current

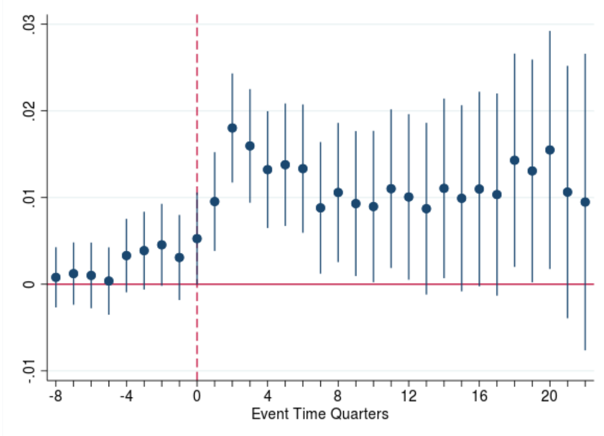


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. *Prime* is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

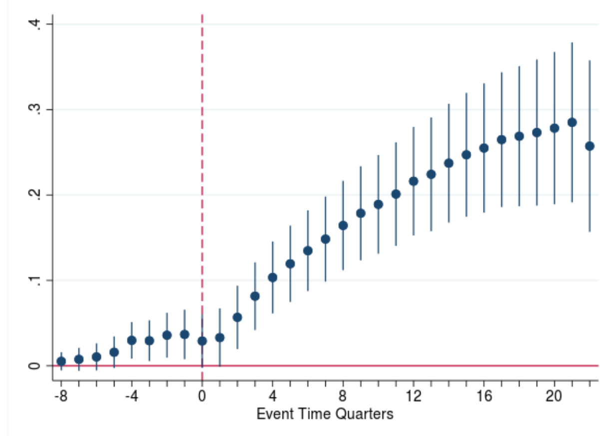
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A4. Mortgage Loan Use After Severe Identity Theft Resolution: Subprime-to-Prime Transition Group

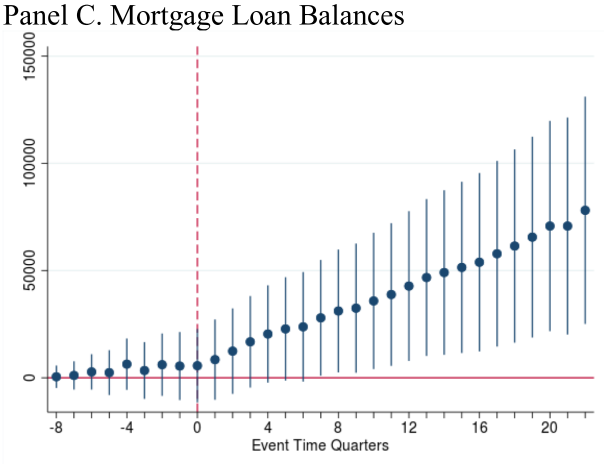
Panel A. New Mortgage Loan Holder



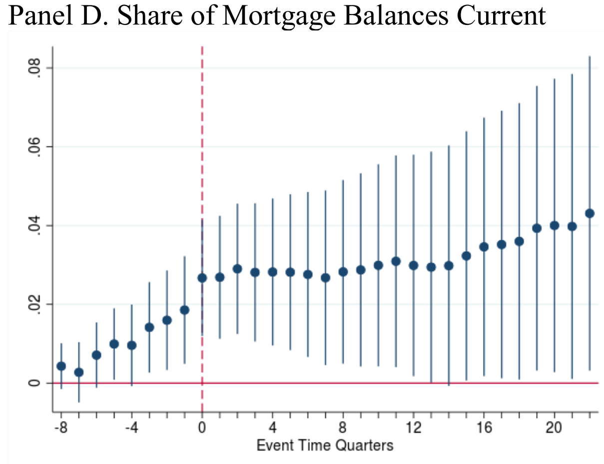
Panel B. Number of Mortgage Loans



Panel C. Mortgage Loan Balances



Panel D. Share of Mortgage Balances Current

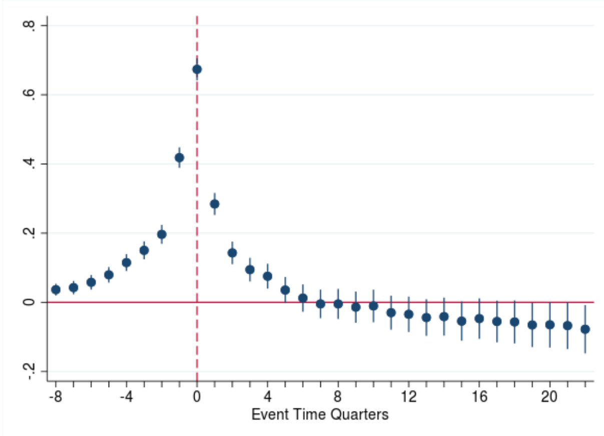


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. *Prime* is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The dots represent point estimates, and bands show 95 percent confidence intervals. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

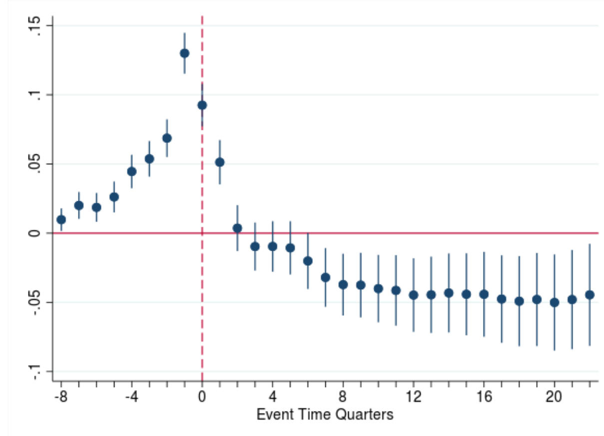
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A5. Indicators of Potential Severe Identity Theft — Balanced Panel

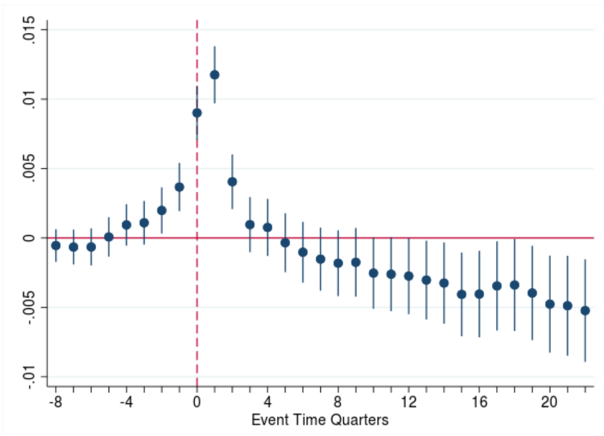
Panel A. Credit Inquiries



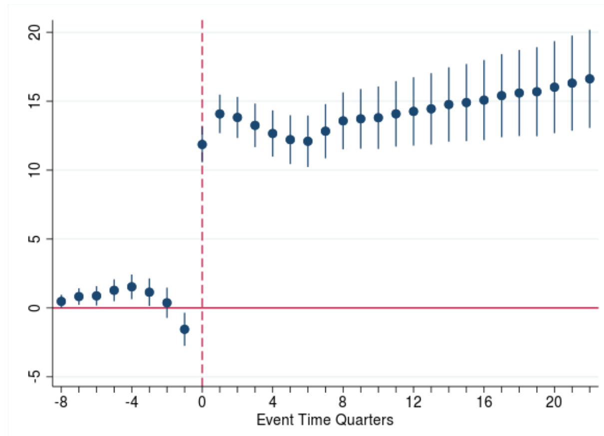
Panel B. New Revolving Accounts



Panel C. Address Reversals



Panel D. Risk Score

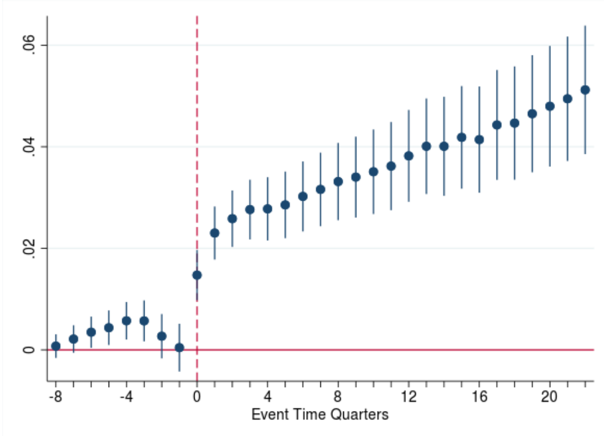


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data set includes credit data from Q1:2003 to Q1:2019 for extended fraud alert filers in Q1:2008–Q3:2013. The panel is balanced so that each alert filer has data from event quarter -22 to event quarter 22. The dots represent point estimates, and bands show 95 percent confidence intervals. Risk Score is the Equifax Risk Score. Address Reversals are based on U.S. Census blocks of fraud victims (not scrambled addresses as in the previous graphs) because scrambled addresses are not available before Q1:2008 and after Q3:2013.

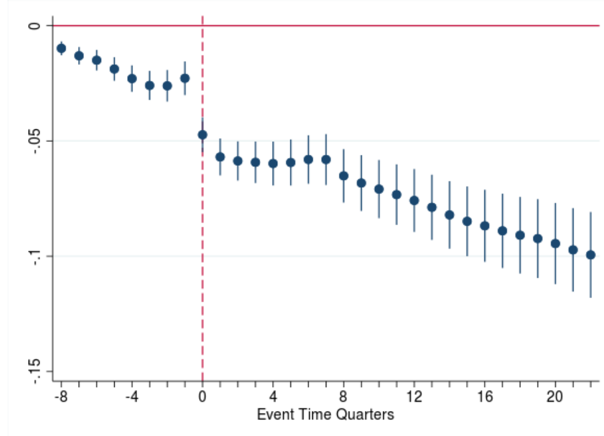
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A6. Credit Performance Before and After Severe Identity Theft — Balanced Panel

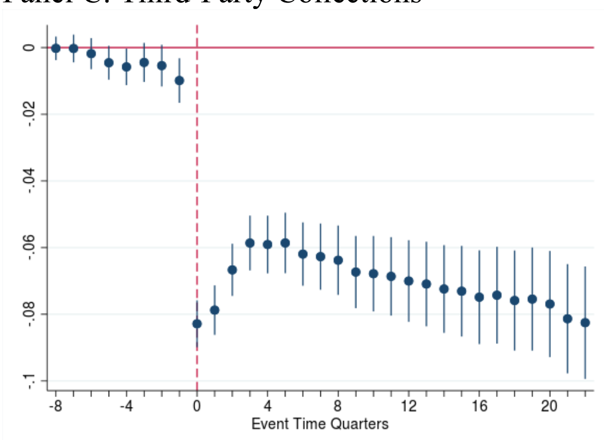
Panel A. Share of Card Balances Current



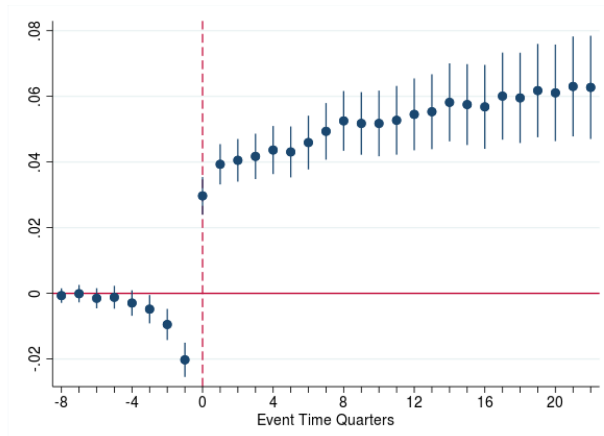
Panel B. Major Derogatory Events



Panel C. Third-Party Collections



Panel D. Share of Prime Consumers

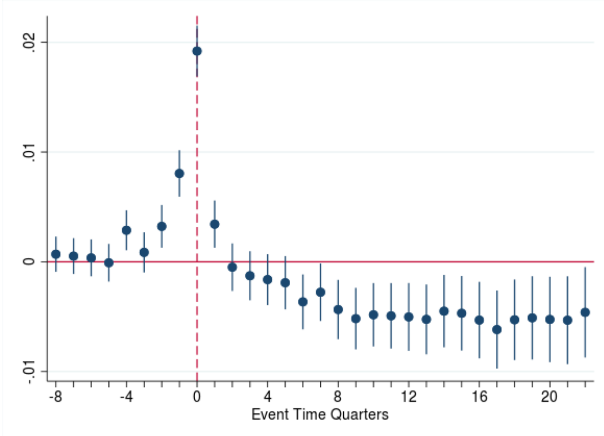


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Prime is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data set includes credit data from Q1:2003 to Q1:2019 for extended fraud alert filers in Q1:2008–Q3:2013. The panel is balanced so that each alert filer has data from event quarter –22 to event quarter 22. The dots represent point estimates, and bands show 95 percent confidence intervals. Risk Score is the Equifax Risk Score.

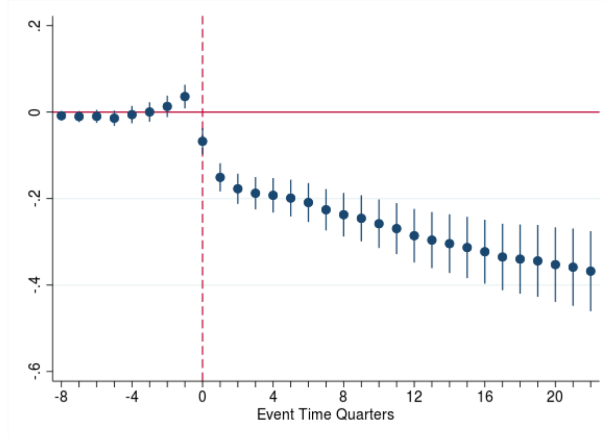
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A7. Credit Card Use After Severe Identity Theft Resolution — Balanced Panel

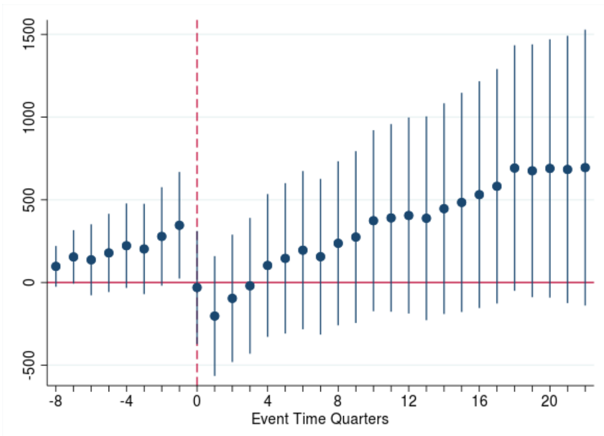
Panel A. New Cardholder



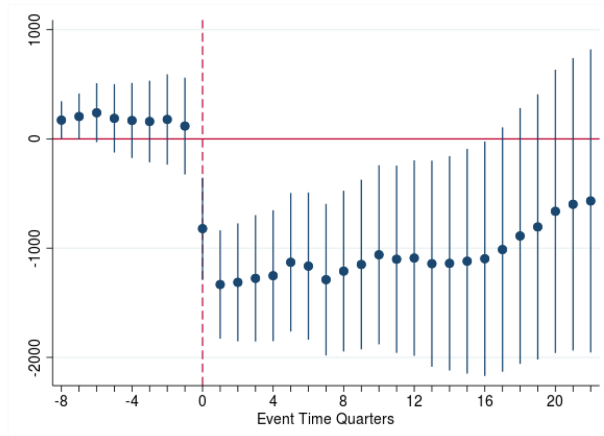
Panel B. Number of Cards



Panel C. Card Balances



Panel D. Card Credit Limits

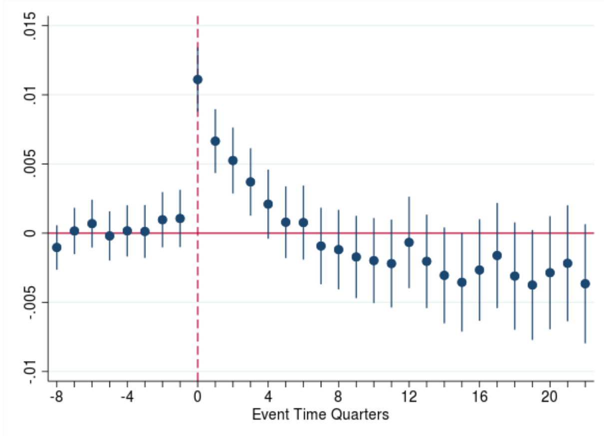


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data set includes credit data from Q1:2003 to Q1:2019 for extended fraud alert filers in Q1:2008–Q3:2013. The panel is balanced so that each alert filer has data from event quarter –22 to event quarter 22. The dots represent point estimates, and bands show 95 percent confidence intervals.

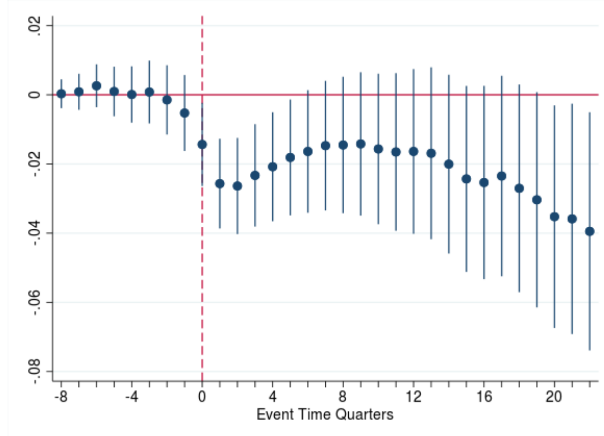
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A8. Auto Loan Use After Severe Identity Theft Resolution — Balanced Panel

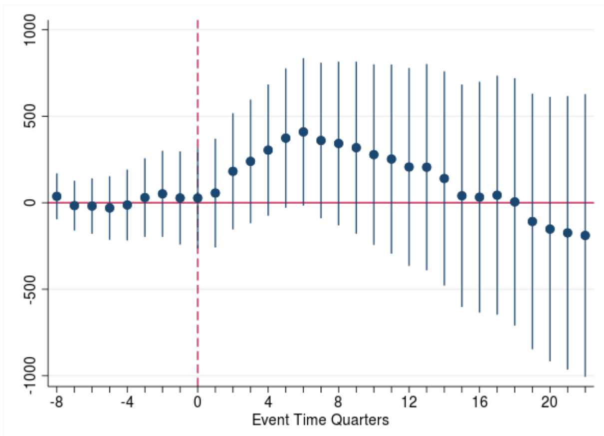
Panel A. New Auto Loan Holder



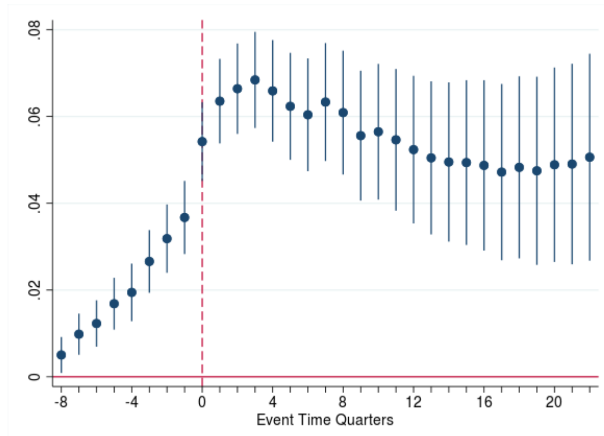
Panel B. Number of Auto Loans



Panel C. Auto Loan Balances



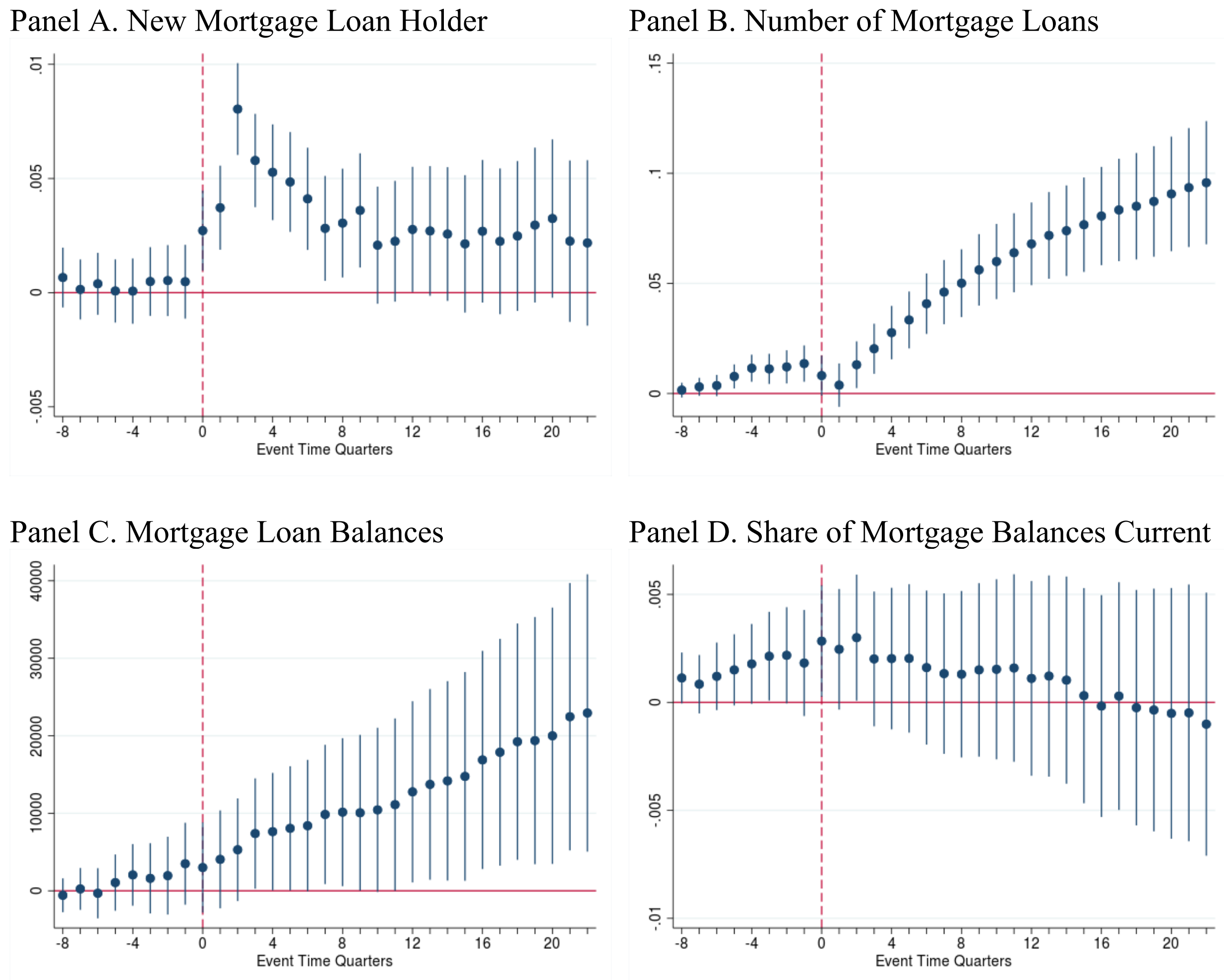
Panel D. Share of Auto Balances Current



Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. *Prime* is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data set includes credit data from Q1:2003 to Q1:2019 for extended fraud alert filers in Q1:2008–Q3:2013. The panel is balanced so that each alert filer has data from event quarter –22 to event quarter 22. The dots represent point estimates, and bands show 95 percent confidence intervals.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A9. Mortgage Loan Use After Severe Identity Theft Resolution — Balanced Panel

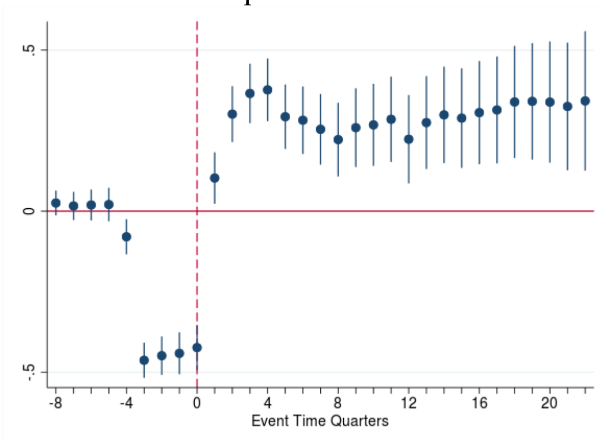


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. *Prime* is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data set includes credit data from Q1:2003 to Q1:2019 for extended fraud alert filers in Q1:2008–Q3:2013. The panel is balanced so that each alert filer has data from event quarter –22 to event quarter 22. The dots represent point estimates, and bands show 95 percent confidence intervals.

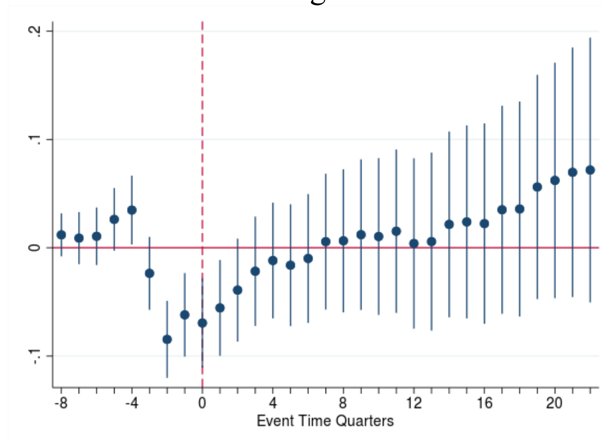
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A10. Indicators of Potential Severe Identity Theft — Filers Without Credit Inquiries

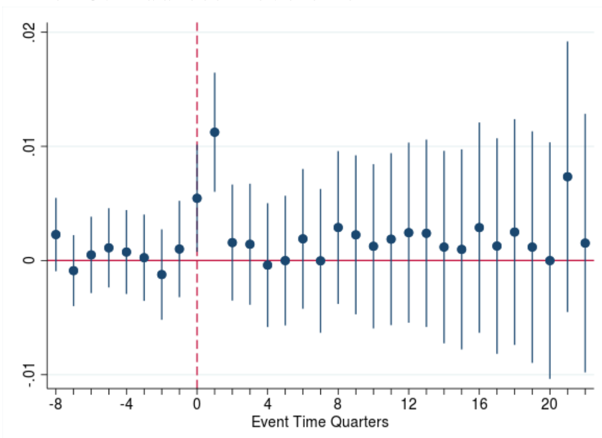
Panel A. Credit Inquiries



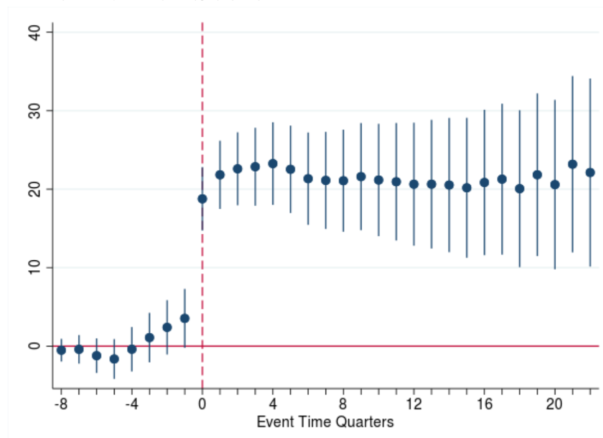
Panel B. New Revolving Accounts



Panel C. Address Reversals



Panel D. Risk Score

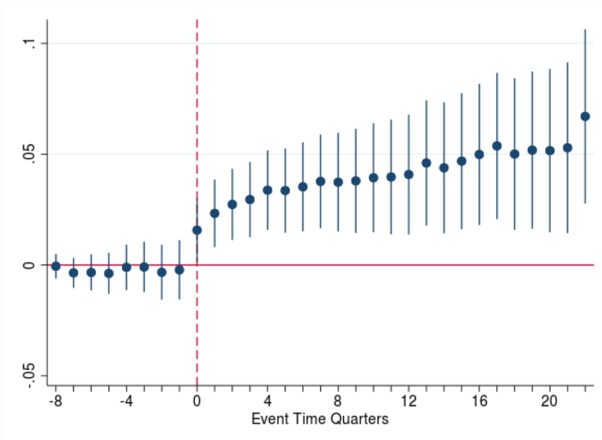


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data include only extended fraud alert filers in Q1:2008–Q3:2013. The sample includes filers without credit inquiries in the three quarters before and the quarter of alert filing. The dots represent point estimates, and bands show 95 percent confidence intervals. Risk Score is the Equifax Risk Score.

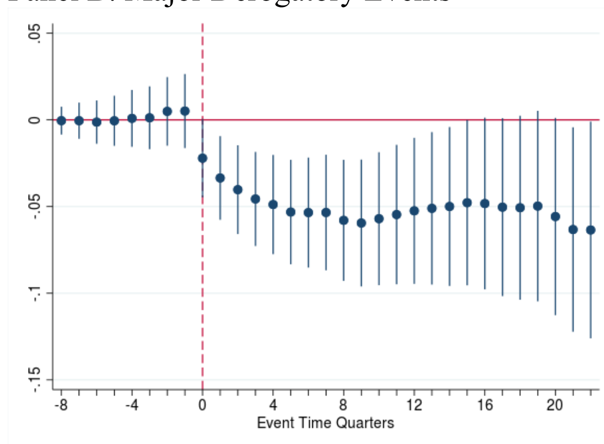
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A11. Credit Performance Before and After Severe Identity Theft — Filers Without Credit Inquiries

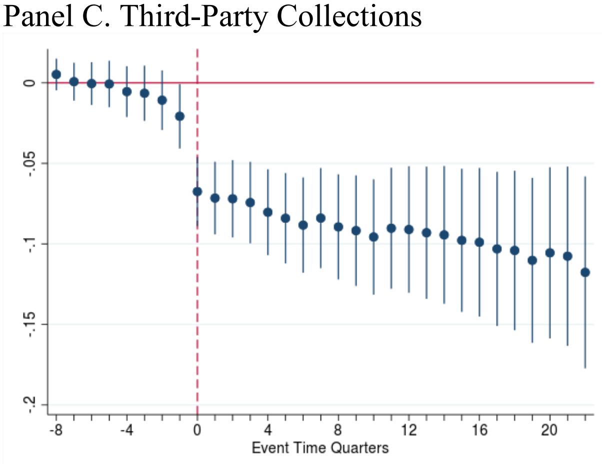
Panel A. Share of Card Balances Current



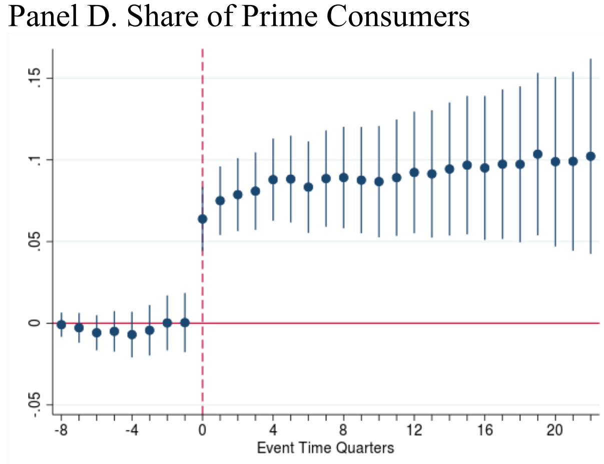
Panel B. Major Derogatory Events



Panel C. Third-Party Collections



Panel D. Share of Prime Consumers

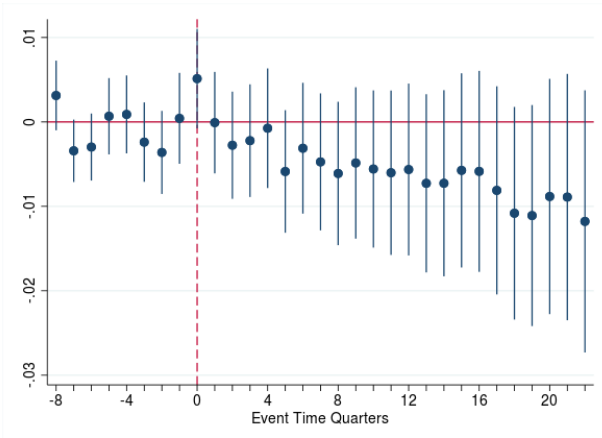


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. *Prime* is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data include only extended fraud alert filers in Q1:2008–Q3:2013. The sample includes filers without credit inquiries in the three quarters before and the quarter of alert filing. The dots represent point estimates, and bands show 95 percent confidence intervals. Risk Score is the Equifax Risk Score.

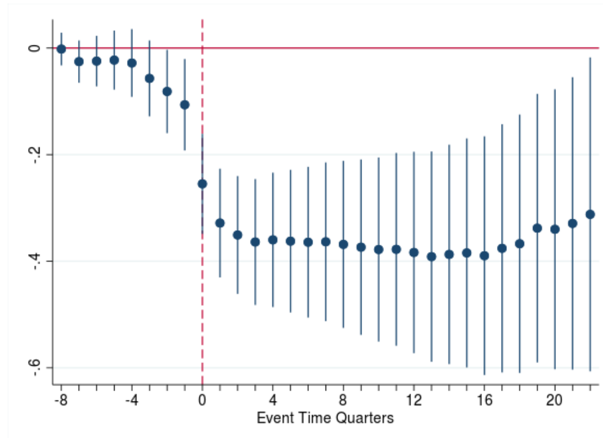
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A12. Credit Card Use After Severe Identity Theft Resolution — Filers Without Credit Inquiries

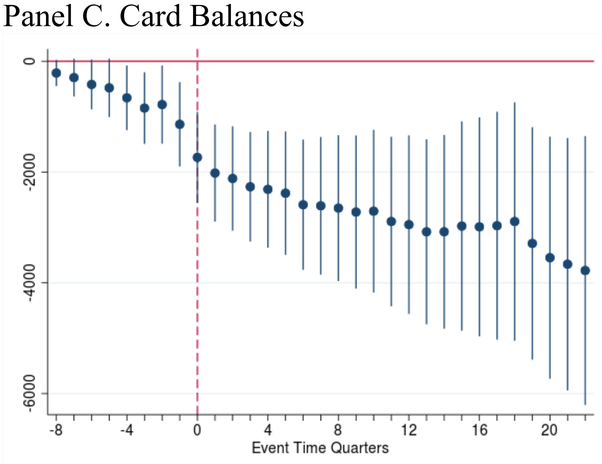
Panel A. New Cardholder



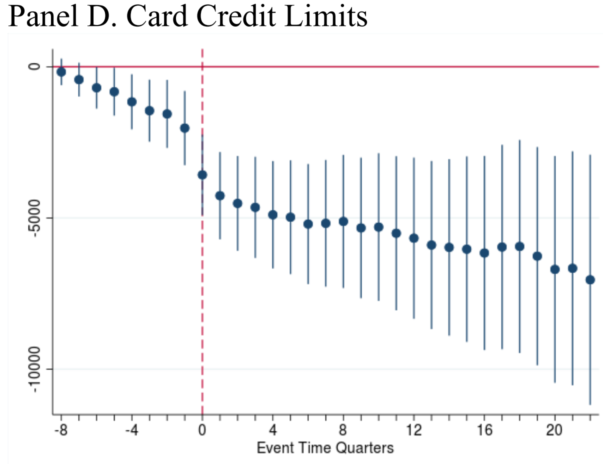
Panel B. Number of Cards



Panel C. Card Balances



Panel D. Card Credit Limits

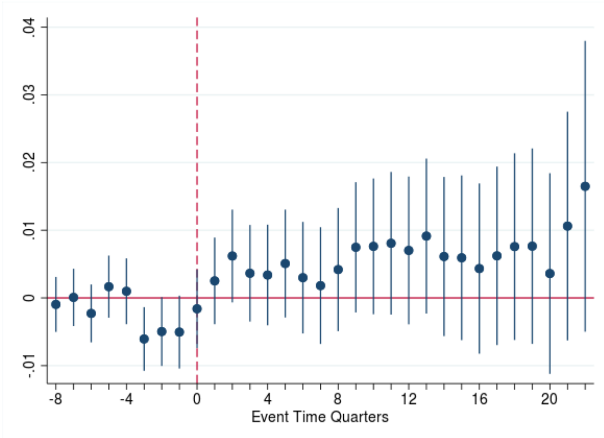


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data include only extended fraud alert filers in Q1:2008–Q3:2013. The sample includes filers without credit inquiries in the three quarters before and the quarter of alert filing. The dots represent point estimates, and bands show 95 percent confidence intervals.

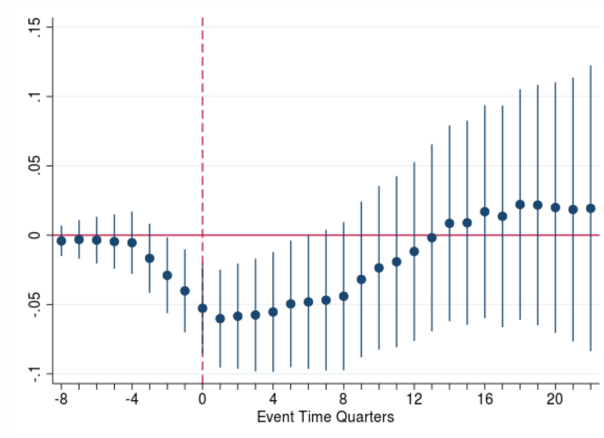
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A13. Auto Loan Use After Severe Identity Theft Resolution — Filers Without Credit Inquiries

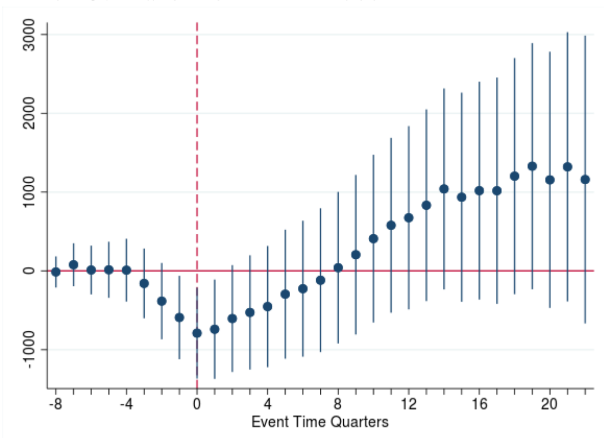
Panel A. New Auto Loan Holder



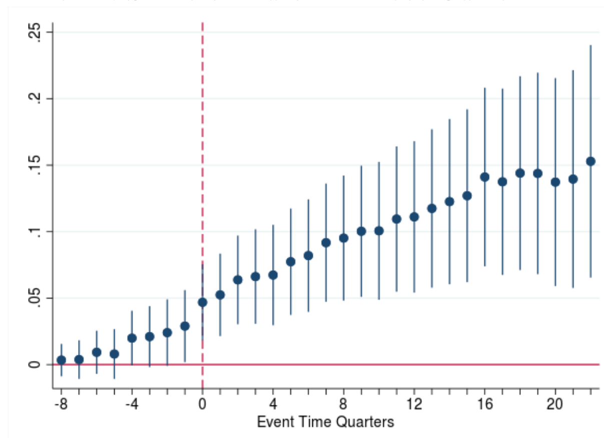
Panel B. Number of Auto Loans



Panel C. Auto Loan Balances



Panel D. Share of Auto Balances Current

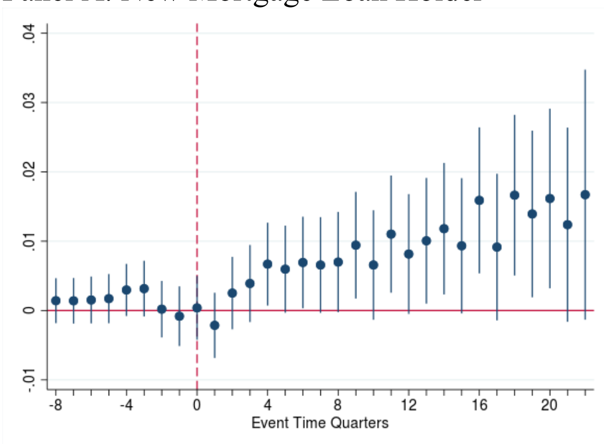


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data include only extended fraud alert filers in Q1:2008–Q3:2013. The sample includes filers without credit inquiries in the three quarters before and the quarter of alert filing. The dots represent point estimates, and bands show 95 percent confidence intervals.

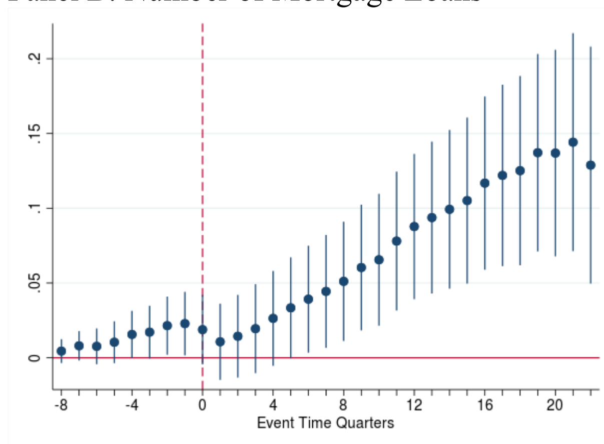
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A14. Mortgage Loan Use After Severe Identity Theft Resolution — Filers Without Credit Inquiries

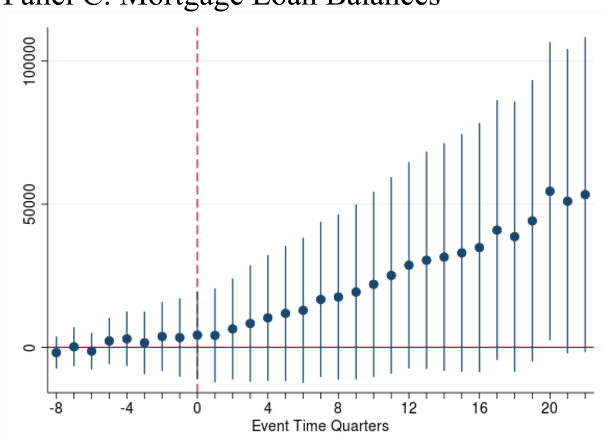
Panel A. New Mortgage Loan Holder



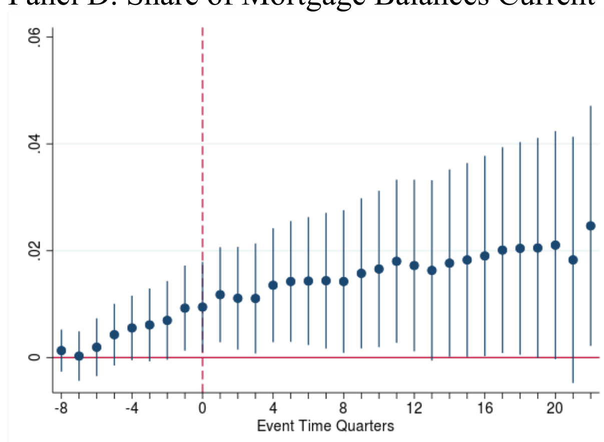
Panel B. Number of Mortgage Loans



Panel C. Mortgage Loan Balances



Panel D. Share of Mortgage Balances Current

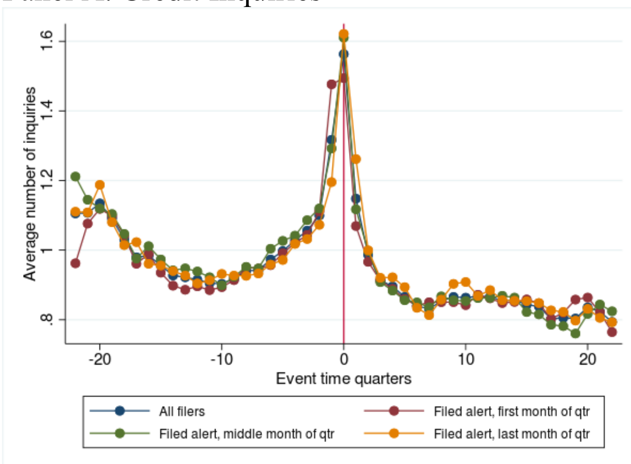


Notes: This figure depicts changes in the credit bureau characteristics of severe identity theft victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All coefficients are estimated relative to the base category, which is quarters −22 to −9. The data include only extended fraud alert filers in Q1:2008–Q3:2013. The sample includes filers without credit inquiries in the three quarters before and the quarter of alert filing. The dots represent point estimates, and bands show 95 percent confidence intervals.

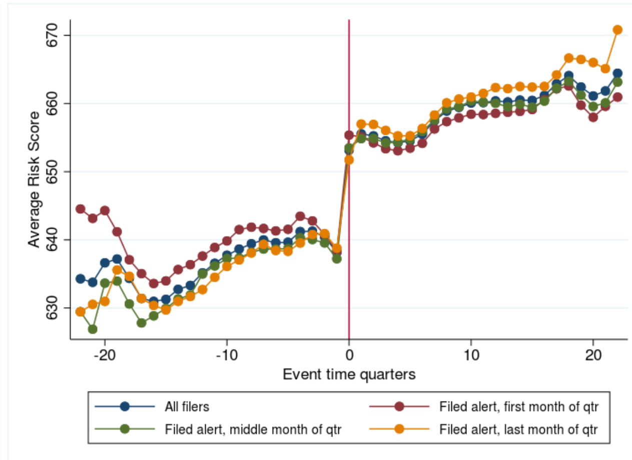
Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax

Figure A15. The Effect of Severe Identity Theft on Credit Bureau Activity by Month of Alert Filing

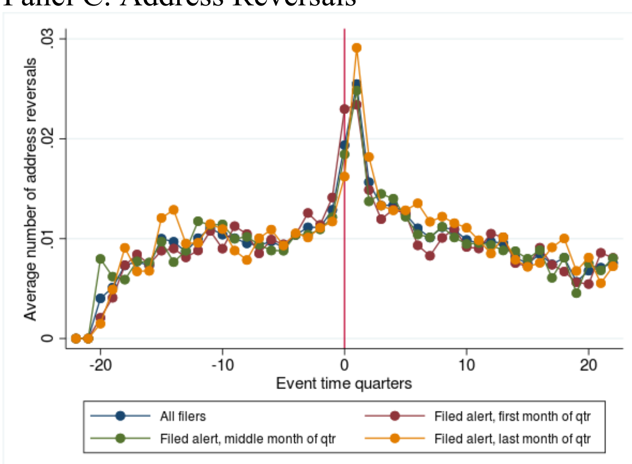
Panel A. Credit Inquiries



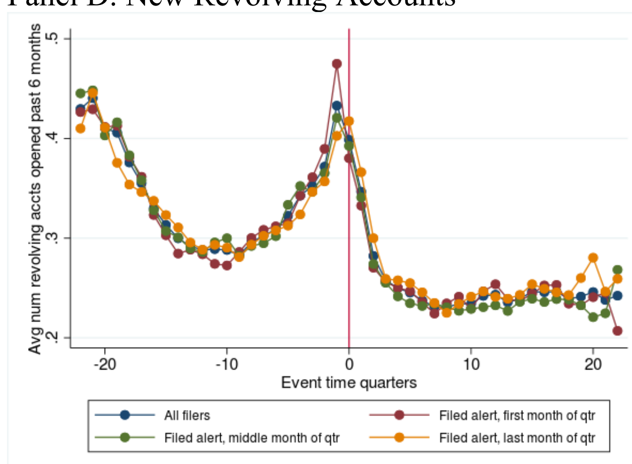
Panel B. Risk Score



Panel C. Address Reversals



Panel D. New Revolving Accounts



Notes: This figure depicts the average values of the credit bureau characteristics of severe identity theft victims before and after fraud activity by the month of the extended alert filing. Time 0 denotes the quarter of extended fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. Risk Score is the Equifax Risk Score. The data include only extended fraud alert filers in Q1:2008–Q3:2013.

Sources: Authors' calculations using data from FRBNY Consumer Credit Panel/Equifax Data, augmented with variables obtained by the Consumer Finance Institute from Equifax