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# Financial Consequences of Identity Theft: Evidence from Consumer Credit Bureau Records

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## ABSTRACT

This paper examines how a negative shock to the security of personal finances due to severe identity theft changes consumer credit behavior. Using a unique data set of consumer credit records and alerts indicating identity theft and the exogenous timing of victimization, we show that the immediate effects of fraud on credit files are typically negative, small, and transitory. After those immediate effects fade, identity theft victims experience persistent, positive changes in credit characteristics, including improved Risk Scores. Consumers also exhibit caution with credit by having fewer open revolving accounts while maintaining total balances and credit limits. Our results are consistent with consumer inattention to credit reports prior to identity theft and reduced trust in credit card markets after identity theft.

*Keywords:* identity theft, fraud alert, Risk Score, consumer protection, credit report

*JEL Codes:* G02, D14, D18

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## 1. Introduction

Due to a number of recent massive data breaches, sensitive personal information of hundreds of millions of consumers, such as names, dates of birth, or Social Security numbers, became subject to potential criminal use, including identity theft. The prevalence and magnitude of identity theft in the United States has been widely documented and publicized in recent years. The U.S. Bureau of Justice Statistics reported that, in 2014, 17.6 million U.S. consumers (about 7 percent of adults) were victims of at least one incident of identity theft. These victims reported gross financial losses of approximately \$15 billion (Harrell, 2015) and experienced significant emotional distress owing to the fraud.<sup>1</sup> Yet, much less is known about the consequences of identity theft for individual consumers or about consumers' response to identity theft, particularly in the context of their credit behavior.

We contribute new insights on the short- and long-run effects of identity theft on consumer credit outcomes by assembling a new, unique data set combining anonymized consumer credit records with information about instances of identity theft. In particular, we focus on individuals with extended fraud alerts, which require a police or comparable report with credible evidence of identity theft. To identify the effect of identity theft on consumer credit outcomes, we use the plausibly exogenous timing of fraud occurrence to compare the outcomes of individuals with extended fraud alerts placed later in our sample (control group) with already victimized consumers (treatment group). Rather than simply comparing identity theft victims with nonvictims, this method overcomes possible selection bias induced by the unobservable and potentially confounding factors that determine a fraud victim's propensity to file an extended fraud alert.

Exploiting the plausibly exogenous timing of identity theft and our unique data, we examine the effect of identity theft on consumer credit bureau records in three periods: shortly before and including fraud alert filing (Victimization), short-run period immediately after identity theft (The Short Run), and long-term postidentity theft (The Long Run). First, we document that, during Victimization, identity theft victims have more credit inquiries (applications for credit) in their credit files, more new credit cards opened in their name, and more reverse address changes (reversals of a temporary address change to the original address) when compared with our control group. These changes are consistent with criminals applying for credit with stolen consumer information, obtaining new credit cards for some consumers, and fooling lenders into sending these

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<sup>1</sup> Net losses for consumers are much less frequent and typically small in magnitude. See Section 8.5 of this paper. Harrell (2015) is based on the Identity Theft Supplement to the National Crime Victimization Survey (NCVS). For detailed information on the NCVS and its methodology, visit <https://www.bjs.gov/index.cfm?ty=dcdetail&iid=245>.

cards to new addresses where criminals can collect them. These fraudulent activities negatively affect consumers' overall financial health as represented by Risk Score; Risk Scores decline by 4 points, on average, with severely affected consumers experiencing Score declines of 14 points and others becoming subprime as a result of the fraud.<sup>2</sup>

In The Short Run, we find that many of the negative consequences of identity theft observed in the earlier period quickly disappear from credit bureau records. In particular, credit inquiries, the number of new credit cards, balances on existing credit cards, and address reversals all decrease significantly. 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 proportion of cards in good standing increases. On the other hand, the number of open bankcards and the number of cards with positive balances decrease by more than their respective fraud-related increases, while the total credit limit returns approximately to pre-fraud levels. The removal of fraudulent information from affected individuals' credit bureau files alone is insufficient to explain these incremental positive changes.

Consistent with the changes in individual credit characteristics, we find that fraud victims' Risk Scores increase in The Short Run by an average of 12 points relative to the control group. For many of these consumers, this Risk Score increase is larger than the decrease in the Score due to fraud (which is 4 points on average). We also observe that the proportion of fraud victims with prime Scores increases by 5 percentage points (11 percent) — a substantial increase — after filing an extended fraud alert. Becoming a prime consumer carries a substantial economic benefit, 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 rate (APR)), even for marginal consumers.

In the third period, The Long Run, we establish two important sets of facts about the long-term consequences of identity theft on credit files. First, even five years after identity theft, many aspects of victims' credit files remain substantially and statistically better (e.g., higher Risk Scores and fewer delinquencies) than before the incident, and these changes are persistent. Second, identity theft victims initiate fewer credit applications and open fewer new credit cards compared with their behavior before identity theft, despite their increased Risk Scores. We also observe identity theft victims holding fewer cards in general and fewer cards with positive balances.

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<sup>2</sup> We use the term *Risk 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.

However, we do not observe comparable reductions in measures of credit supply, such as credit card limits, so this behavior is unlikely to be driven by supply-side changes.

There are mechanisms that can explain the short-run impact of identity theft on credit attributes as well as the persistent improved performance on credit and the diminished participation in the credit market: consumer inattention to credit reports and reduced trust in credit markets. These mechanisms are not mutually exclusive. The short-run improvements in Risk Scores, major derogatory events, collection accounts, and cards in good standing suggest that many identity theft victims were not actively policing 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. This explanation is consistent with prior studies (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). The persistent improvement in the management of open accounts, as reflected in improved Risk Scores, suggests that consumers are more attentive to their credit than they were before they were victimized.

The finding that most victims of identity theft retain fewer open bankcards without reducing total card balances is consistent with selective detachment from the credit card market. We argue that the decrease in credit card market attachment reveals the possibility of a deterioration of trust in certain features of this market (e.g., security) by consumers affected by identity theft. Despite enjoying higher Risk Scores, consumers affected by identity theft do not apply for new credit cards and additionally consolidate their use of credit cards to a smaller number of accounts, possibly in the belief that this will decrease their fraud risk. If identity theft contributes to a decline in consumer trust in credit card markets, then our results suggest such negative events may have important spillover effects. Financial markets are, of course, built on trust. Thus, our finding of reduced credit attachment after identity theft raises a concern that the mass exposure of sensitive consumer information could trigger substantial changes in consumers' use of electronic forms of credit and payments.

The rest of this paper is organized as follows. Section 2 summarizes our contributions to the literature. Section 3 describes the data contained in consumer credit bureau records and institutional details on identity theft and extended fraud alerts. Section 4 presents our data. Section 5 describes the summary statistics. The research design and identification strategy are explained in Section 6. Using this strategy, the effects of identity theft on consumer credit characteristics for each of the three periods — Victimization, The Short Run, and The Long Run — are estimated and

presented in Section 7. Section 8 discusses potential mechanisms to explain our results. Heterogeneous effects are discussed in Section 9. Section 10 describes in detail several of the robustness checks we have completed; others are described in the Appendix. Section 11 concludes.

## **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, Laibson, Moloche, and Weinberg, 2006; Bordalo, Gennaioli, and Shleifer, 2013a, 2013b). We add to this broad literature by showing that 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, 2017; Dimmock and Gerken, 2012; Egan, Matvos, and Seru, 2017; 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). Similar to these studies, we show evidence that is consistent with a selective deterioration in trust in financial markets after fraud in the context of borrowing and credit markets but not investment decisions.

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, Hunt, Jacob, Porter, and Summers, 2012; Kahn and Liñares-Zegarra, 2016; Stavins, 2013; Kosse, 2013), this paper examines how identity theft can affect consumers' credit performance and credit variables. This study is also

related to papers considering the trade-off 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**

#### **3.1 Data Contained in Consumer Credit Bureau Records**

In this paper, we examine the financial consequences of identity theft on consumer credit attributes using credit bureau records. A consumer credit report 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 protections for consumers affected by identity theft. FACTA permits consumers to obtain free copies of their credit reports from each of the three major bureaus once a year. FACTA also required federal regulators to develop "red flag" indicators of identity theft to aid in detecting identity theft. It also required credit reporting agencies to block information that results from identity theft and to implement a set of indicators or credit file flags that inform creditors that a consumer was, or may have been, a victim of identity theft. The credit file flags include initial and extended fraud alerts that we use in this paper.<sup>3</sup>

The elaborate process of filing for an extended fraud alert implies that practically all filers of these alerts have been victimized.<sup>4</sup> In particular, extended fraud alert filers must submit a police

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<sup>3</sup> During our sample period, an initial fraud alert may be placed in a credit file for 90 days (and may be renewed for multiple and consecutive 90-day periods) if a consumer makes a good faith assertion of identity theft. The Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018 extended the duration of initial fraud alerts to 12 months. This legislation does not affect our analysis sample.

<sup>4</sup> Cheney, Hunt, Mikhed, Ritter, and Vogan (2014) provide evidence suggesting that most consumers who file initial alerts, credit freezes, or credit monitoring are often acting out of precaution rather than being actual victims. We

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.<sup>5</sup> Thus, filers of these alerts are unlikely to place alerts in their credit bureau files simply due to worry, an abundance of precaution, or another reason.

After an identity theft report or a police report has been filed, the consumer can add an extended fraud alert to his or her file. 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 above applications. Once filed, an extended fraud alert remains in a consumer's credit file for seven years unless the consumer chooses to remove it beforehand. 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, this information 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 — at no cost — copies of his or her credit reports when filing a 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

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choose to focus on extended fraud alerts in this study to be conservative about potential false positives, but we recognize that this implies additional false negatives.

<sup>5</sup> 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.”



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 (FRBNY)/Equifax Consumer Credit Panel (CCP) data set, combined with a unique data set of information on the timing (placement) and type of fraud alerts that the Consumer Finance Institute obtained from Equifax. The CCP data set contains credit characteristics from an anonymized 5 percent random sample of credit bureau records of U.S. consumers.<sup>6</sup> 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 records. 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 examine the credit files of 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). Our sample consists of about 10.8 million consumers. We observe that approximately 53,000 of that sample filed a first extended fraud alert in Q1:2008 or thereafter.<sup>7</sup> In much of the following analysis, we examine changes in variables in *event time* — the number of quarters before or after an extended fraud alert first appears.

Within the CCP data set, 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 and 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 census tract). We also have the Equifax

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<sup>6</sup> The sample is constructed by selecting consumers with at least one public record or one credit account currently reported and with one of five numbers in the last two digits of their Social Security number (SSN) 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.

<sup>7</sup> We call these *first* extended fraud alerts to distinguish between the quarter in which the alert is placed in the file and the subsequent quarters during which the alert is effective. In other words, we use the term to distinguish between the flow and stock of consumers with fraud alerts in our data.

Risk Score and the number of inquiries (i.e., applications for credit or insurance). Comparing the treatment and control groups in our study, we examine the number of and balances on revolving accounts, the proportion of cards in good standing, total credit limit, and many other consumer characteristics.

FACTA requires that 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 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, the CCP is similar to other real-time data sets used by researchers. It is important to emphasize that this property of the CCP 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.

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 indicate that both the timing of fraud and the effect of placement of fraud alerts do not systematically differ by the filing month (see Figure A1 in the Appendix).

## 5. Summary Statistics and Indicators of Potential Identity Theft

Table 1 presents the descriptive statistics for our data set, including information on consumers without any type of fraud alert and on extended alert filers both four quarters before filing and at the time of filing. From this table, we can observe a number of differences between consumers without fraud alerts and the extended alert population for many of these variables. For example, the average Risk Score for the population without an alert is 695, while it is 655 for the extended alert population at event time zero. The number of inquiries in the past three months is 0.54 for the nonfiler population compared with 1.5 for the extended alert population at time zero. This implies that a typical filer of an extended fraud alert is not comparable to an average nonfiler. For example, most nonfiling consumers have prime Risk Scores, while the average extended alert filer has a subprime Score. These differences can potentially reflect both the selection of consumers into fraud alert protection as well as the effect of the fraud alert itself. We disentangle these two factors in the subsequent analysis.

We also look at credit outcomes of fraud victims over time and plot four variables in Figure 1. Panel A of Figure 1 plots the average number of credit inquiries for all fraud victims in event time, with event time  $e = 0$  equal to the quarter of the first extended fraud alert filing. In all panels of this figure, we remove business cycle and seasonal effects by including calendar time dummies, such that the plots display the residual average values of variables excluding seasonal and business cycle effects. Panel A of Figure 1 displays a very large and transitory increase in the number of credit applications that coincides with the quarter the extended alert is filed. The average number of inquiries increases from 1.2 before fraud to 1.8 (a 50 percent increase) at the time of the fraud alert. This increase is consistent with consumers' personal information being stolen by criminals and used to apply for credit.<sup>8</sup> 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 National Crime Victimization Survey (NCVS) show that almost 50 percent of identity theft victims discover identity theft through such communications.

Panel B of Figure 1 plots the average number of new revolving accounts for fraud victims before and after they file an alert. This figure shows that new revolving accounts begin to increase sharply a few quarters before the fraud alert filing and peak one quarter before filing. This finding is consistent with criminals using consumers' stolen personal information to open new revolving

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<sup>8</sup> We provide formal statistical tests of these effects relative to the control group in the next section; the results generally follow trends presented in this section. Additional tests can be found in Cheney et al. (2014).

accounts. The number of new accounts declines quickly once the fraud is discovered and reported to the credit bureaus.

Certain types of 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.<sup>9</sup> 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.<sup>10</sup> Panel C of Figure 1 plots the fraction of fraud alert filers who revert their address to the prior quarter's address over event time. We find evidence of a sharp increase in reverse address changes at the time the fraud alert is filed and one quarter after, consistent with the consumer reversing address changes made by criminals.<sup>11</sup>

Finally, panel D of Figure 1 shows a transitory decline in Risk Score shortly before the fraud alert filing and a subsequent recovery in the quarters after filing. Note that the average increase in a Score that follows is typically larger than the transitory decline; we revisit this point in the next section. The increases in inquiries, reverse address changes, and number of new accounts near the time of the fraud alert filing as well as the decline in Risk Score shortly before the placement of the fraud alert, allow us to conclude that fraud is very likely to have occurred either during the quarter the fraud alert was filed or at most a quarter or two before that date.

## 6. Research Design

### 6.1 Identification Strategy

To identify the effects of identity theft on consumer credit outcomes, we exploit 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 extended alert filing. Ideally, to identify

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<sup>9</sup> 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.

<sup>10</sup> 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.

<sup>11</sup> Note that the removal of the business cycle effects results in reverse address changes being close to zero or negative in most event time quarters. These negative values can be interpreted as deviations from the pattern induced by the business cycle. Even though some values are negative, they are not statistically significant. We formally test this in the next section.

the effect of fraud, we would compare extended alert filers with all nonfilers or a selected group of nonfilers. However, since not every victim of identity theft or fraud files an extended fraud alert with a credit bureau,<sup>12</sup> extended alert filers may be more motivated or attentive than victimized nonfilers. It is likely that such unobservable factors would be correlated with the way individuals manage their credit, pay their bills, or borrow money. If we were to compare extended alert filers with all nonfilers, we would not be able to separate the effects of fraud from the effect of unobservable motivation to file an alert, and our estimates would suffer from selection bias.

We propose an identification strategy that relies on the variation in the timing of victimization and alert filing (treatment) to identify the effect of fraud on credit bureau characteristics. In this strategy, we focus on the sample of fraud alert filers only because we believe that victimization itself, as well as its timing, is exogenous to the consumer. 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 occurrence to compare the outcomes of already victimized extended alert filers (treatment group) with the outcomes of not-yet-victimized extended alert filers (control group).

We present additional evidence that potential endogenous timing of filing and reverse causality do not represent threats to causal inference in our study. We also discuss each of these possible empirical challenges in the following subsections.

### **6.1.2. Exogeneity of Extended Alert Timing**

One concern about this strategy is that the timing of the extended fraud alert may not be exogenous. For example, 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 would 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

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<sup>12</sup> According to Harrell (2015), about 8 percent of all identity theft victims contact a credit bureau following identity theft. Of those consumers, 68 percent placed a fraud alert in their file, while 18 percent provided a police report to the credit bureau. Among consumers suffering from more severe forms of identity theft, such as opening new accounts in the consumer's name, about 33 percent of victims contact a credit bureau, and about a third of those provide a police report to the credit bureau.

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 2 shows that, for identity theft victims, almost 50 percent of respondents discover misuse of their information within 24 hours, and 95 percent of respondents discover fraud within one quarter. Panel B of Figure 2 shows that, for individuals who file an alert with a credit bureau, more than 86 percent of respondents report discovering identity theft within a quarter. Identity theft victims also manage to clear up their credit and financial problems within the same timeframe as discovery (Figure 2, panel C). Similar to discovery timing, 97 percent of respondents report clearing up all financial problems due to identity theft within one quarter. Taken together, these results show that identity theft victims discover fraud and take corrective actions quickly.

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.

### **6.1.3 Reverse Causality**

The other potential challenge to identification 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 1 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 1 show that fraud-related activity is tightly concentrated just before the alert filing or at the time of filing and not distributed across the quarters prior to alert filing. We also test this hypothesis in Section 10 with a regression analysis and find similar results.

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.

## 6.2 Econometric Methodology

In our main analysis, we estimate the following event study regression model:

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

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 more than eight quarters 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,  $\delta_i$ .<sup>13</sup> Standard errors are clustered at the individual level.

As previously mentioned, the data used in these regressions only include extended fraud alert filers. Hence, 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 (2014); and Dobkin, Finkelstein, Kluender, and Notowidigdo (2016).

## 7. The Effects of Identity Theft on Consumer Credit Characteristics

In this section, we report our main findings for three periods. First, we reexamine how fraud affects consumer credit characteristics before consumers report it to credit bureaus (Victimization, defined as event time (quarters) -4 to 0). Second, we explore how fraud victimization affects consumer credit behavior immediately after identity theft (The Short Run, defined as event time 1-4). Third, we document longer term consequences of fraud (The Long Run, defined as event time 5 onward). We summarize our results for these three periods in Figures 3 through 5. All three figures report coefficients from the distributed lag regression model specified

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<sup>13</sup> 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 almost identical results.

in Equation (1) for a number of outcome measures. The coefficients show the difference in the outcome variables between already victimized consumers (treatment group) and not-yet-victimized individuals (control group) over the time before and after identity theft. In addition to point estimates displayed as dots, all three figures provide 95 percent confidence intervals as vertical bands. In the following subsections, we discuss patterns in our results during the three identified periods: Victimization, The Short Term, and The Long Term.

### **7.1 Victimization and Short-Run Periods**

Panel A of Figure 3 plots the differences in credit inquiries between treated and not-yet-treated identity theft victims before and after they report being victimized (through alert filing). Similar to panel A of Figure 1, this figure shows that, on average, inquiries increase by 0.6 at the time of fraud, and this increase is highly statistically significant. The coefficient can be interpreted as 6 out of 10 consumers accumulating one additional credit application shortly before the fraud occurs. This finding is consistent with criminals applying for credit with stolen personal information. The number of inquiries decreases after fraud and remains at a lower level than before fraud. Similar to panel B of Figure 1, panel B of Figure 3 shows that the number of new revolving accounts peaks in the quarter preceding the extended fraud alert filing. On average, 1 out of 10 fraud victims have one new revolving account opened during that time. The number of new revolving accounts declines quickly after fraud alert filing. Fraud victims have, on average, between 0.05 and 0.1 fewer new revolving accounts in the quarter after identity theft or fraud.

Panel C of Figure 3 plots the effect of fraud on reverse address change, with the only statistically significant coefficients in the quarter before and a few quarters after extended fraud alert filing. 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. Consistent with criminal activity, panel D of Figure 3 shows a statistically significant decline in Risk Score of about 4 points one quarter before the fraud event. However, this decline is reversed, and, on average, Risk Scores increase by about 12 points relative to the omitted period at the time of the fraud alert. The figure shows that this improvement in Risk Scores is persistent and remains highly statistically significant for several years.

An important feature in all panels of Figure 3 is that there are no pretrends in credit inquiries, Risk Score, reverse address changes, and the number of new accounts a year or more before alert filing. This finding is consistent with the identifying assumption that not-yet-treated individuals are a reasonable control group for already victimized consumers. In addition, this result



suggests that fraud-related activity happens shortly before an extended fraud alert (up to one year before the alert filing).

In addition, the results in Figure 3 suggest that negative effects of fraud on Risk Score and increases in credit inquiries, reverse address changes, and new accounts (which are likely due to fraud) are robust and statistically significant. The results also indicate that the persistent improvement in Risk Score after identity theft may be explained in part by reductions in the number of inquiries and the number of new accounts after fraud. The reductions in both of these credit variables can positively affect Risk Scores.

## **7.2 The Long-Run Effects of Identity Theft**

In addition to the effects of identity theft during Victimization and The Short Run, panels A, B, and D of Figure 3 allow us to observe differences in the credit card behavior of fraud victims in The Long Run. In particular, these panels show Risk Score, the number of credit inquiries, and the number of new revolving accounts for up to 22 quarters after fraud occurrence. While panel D of Figure 3 shows that, on average, victimized consumers' Risk Scores are 13 points higher even five years after fraud, these consumers do not apply for credit as much as they did before fraud, and they have 0.3 fewer inquiries per quarter in this period (panel A, Figure 3). Consistent with this reduced number of inquiries, the number of new revolving accounts is 0.12 lower for fraud victims in the long run (panel B).

Figure 4 presents the effects of fraud on such credit outcomes as the number of open bankcards, cards with positive balances, total revolving credit balance, and total revolving credit limit. While the number of open cards increases prior to fraud alert filing (panel A, Figure 4), it drops sharply at the time of fraud alert filing and continues to decline thereafter. This result may imply that consumers close fraudulent cards that criminals opened at time  $e = -1$ . After the fraud, consumers have fewer cards than before the fraud took place, suggesting that fraud victims close cards they do not actively use. Alternatively, they may dispute accounts reported as open when they had been closed for some time. This finding is also consistent with a reduced number of new revolving accounts opened after fraud discovery, as shown in panel B of Figure 3.

Panel B of Figure 4 shows that cards with positive balances (actively used cards) also follow a similar pattern, even though the decline after fraud alert filing is less pronounced. In The Long Run, fraud victims carry fewer cards with positive balances than they did before fraud. However, panel C shows that total revolving balances do not change after fraud, as consumers still maintain similar balances, and most changes are statistically insignificant. Finally, panel D shows that, while

Risk Scores and thus access to credit increase, we see no changes in total revolving credit limits; if anything, our point estimates indicate a small, but imprecisely estimated, decline in credit limits. Combined with the evidence of fewer open cards and lower card balances, these figures suggest that consumers may be reducing their engagement with the credit card market in the quarters during and immediately after incidents of identity theft by maintaining fewer credit cards but continuing to use them as shown by the unchanged balances on revolving accounts.

While the previous figures summarize the effects of fraud on credit card use and balances, Figure 5 provides evidence on the performance of fraud victims with these credit products in The Long Run. Panel A of Figure 5 shows that consumers keep a higher proportion of their cards in good standing after fraud. Fraud victims also reduce the incidence of major derogatory events on cards by about 4 percentage points (panel B) and the incidence of third-party collections by 8 percentage points (panel C). The sharp declines in the incidence of derogatory events and third-party collections at the time of an alert filing might result from the consumer 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 cards 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 5. This figure shows that fraud activity at event time  $e = -1$  lowers the share of prime consumers by about 1.8 percentage points (a 4 percent decrease relative to the baseline share of prime consumers of 45 percent). However, after fraud, the share of prime consumers increases by 5 percentage points (an 11 percent increase) and remains elevated throughout our sample period. These changes have potentially far-reaching economic consequences, as they may allow borrowers to obtain more credit and at better terms. On average, the APR on a 30-year, fixed-rate mortgage decreases from 4.7 percent to 3.7 percent when a borrower moves from the 620–639 FICO score range to the 660–679 range.<sup>14</sup> 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.

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<sup>14</sup> This example is based on the national average mortgage interest rates provided by FICO on August 8, 2016.

## **8. Discussion of Potential Mechanisms**

Given the results presented in the previous sections, we discuss a number of plausible mechanisms that may explain the persistence in the increase in Risk Scores and the decline in new and open credit card accounts for consumers who became victims of identity theft. The first two mechanisms described in the subsections that follow (limited attention and trust) are most consistent with our results and are not mutually exclusive. Relying on our results and other empirical data, we show that several other potential mechanisms are unlikely to explain the persistence we observe in our findings.

### **8.1 Limited Attention (Inattention)**

One plausible explanation for our results is that consumers paid little attention to their credit report information prior to suffering 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 38 percent of respondents reported that they had checked their credit reports in the past 12 months (Harrell, 2015). Given the nature and potential economic effects of identity theft, it is likely that a fraud incident may either increase the salience of credit information, increase the cost of acquiring/retaining credit, or encourage increased monitoring of credit reports and/or scores. Identity theft victims experience a number of 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. Evidence from the NCVS shows that the number of 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.<sup>15</sup>

Although we cannot directly test the inattention hypothesis with our data, our empirical results are suggestive that a behavior change occurred after the fraud incident. In particular, the persistent changes we observe across multiple credit outcomes provide descriptive evidence of improved attention in The Short-Run period after identity theft. For example, in Figure 3, we observe that individuals use fewer bankcards after suffering identity theft and open fewer new bankcards. In Figure 5, we observe that individuals experience fewer severe negative credit bureau

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<sup>15</sup> These statistics are based on authors' calculations using the public-use NCVS Identity Theft Supplement data set.

outcomes, such as accounts in collections or past due, in The Short Run after identity theft. Our evidence that these measures are significantly and consistently lower throughout the posttheft period is consistent with consumers paying more attention to their credit information and possibly managing their accounts better, and is inconsistent with the simple removal of fraudulent information from consumers' credit files.

## **8.2 Trust**

Our empirical results may also be explained by a reduction of trust in credit card markets after an identity theft shock. Data from the NCVS show that this concern is relevant for identity theft victims: For those respondents who reported experiencing mental distress, more than 43 percent noted that they would have a more difficult time trusting people. As has been shown in other related literature, trust is an important aspect in financial markets and plays a critical role in the financial decisions that households and individuals make. Thus, we hypothesize that it is plausible that individuals may lose trust in credit markets and consequently become less attached to those markets if they feel that firms are unable to protect their data or that the probability of victimization is higher with increased participation in credit card markets. This decreased attachment could manifest itself in many forms, including less frequent credit applications, fewer new accounts, or closure of existing accounts.

As with the attention mechanism proposed in Section 8.1, we are unable to directly test this hypothesis using our data. However, some of our results are suggestive of decreased trust. Panel A of Figure 3 shows that identity theft victims apply for credit less frequently in The Long Run after fraud, while panel D of Figure 3 shows that consumers open fewer new accounts, with both measures decreasing over time relative to the control group. We also observe in Figure 4 that affected individuals have fewer open bankcards (panel A) and fewer cards with positive balances (panel B), although their total revolving credit balances (panel C) and limits (panel D) remain relatively stable in The Long Run. Combined with the evidence from Figure 3, these results suggest that identity theft victims are selectively less attached to credit markets after fraud: They open fewer new accounts and use fewer existing accounts than before Victimization but maintain comparable available credit (therefore reducing the number of accounts susceptible to fraud) while having higher Risk Scores.

In summary, while individuals may have better access to credit due to their increased Risk Scores, our empirical evidence shows that consumers selectively reduce their credit card market participation to open fewer new accounts and maintain balances on fewer active accounts, while

maintaining only a slightly lower (and imprecisely estimated) total revolving limit. While increased attention to credit records and better management of accounts may result in consumers reducing unnecessary accounts in The Long Run, it does not explain the negative relationship between improved creditworthiness and credit card market participation for an average consumer. Therefore, that we observe declines in credit card market attachment growing over time despite the fact that victims appear to be more creditworthy is indicative of consumers purposefully participating less in credit card markets.

### **8.3 The Supply-Side Response to Placement of Extended Fraud Alerts**

Another possible explanation for the change in consumers' credit variables is a lender (supply) response to the presence of extended fraud alerts in consumer credit files. Because an extended fraud alert removes a consumer's credit report from lists of prescreened credit and insurance offers for five years, in theory, lenders might face difficulties in extending credit to individuals with fraud alerts. Without the availability of credit solicitations, consumers may open fewer accounts, borrow less, and potentially pay off old debt. A reduction in past due balances, fewer third-party collections, and fewer open accounts can all lead to improvements in Risk Scores.

To test for the presence of a supply-side response, we rely upon two sets of results. First, we note results from panel D of Figure 4: a statistically significant decline in credit card limits in the four quarters immediately after identity theft but no statistically significant increases in the total credit limit over time. While credit limits are often interpreted as credit supply, the interpretation is more complicated in our case. Total limits on credit cards may decrease because some cards are closed after identity theft. Account closures are almost certainly driven by consumers, not lenders. On the other hand, lenders may increase limits on cards that remain open. We do not observe such a response.

Second, we test for changes in credit performance when consumers with extended alerts are again eligible for inclusion in lists of prescreened credit and insurance offers, which occurs five years after alert placement (extended alerts are removed from credit bureau files seven years after alert placement). If credit supply is constrained in the initial five years when the prescreen restriction is in place, we should observe changes in credit use after this restriction is removed. In Figures 3 through 5, we do not observe any discrete changes in the variables upon the expiration of the exclusion for receiving prescreened offers. We formally test this hypothesis by performing a standard test of coefficient equality between time  $e = 20$  and  $e = 21$  in our distributed lag model. These tests conclude that, while there are statistically significant differences in the coefficients

between  $e = 20$  and  $e = 21$  for Risk Score, inquiries, and new accounts, none of the estimates are economically significant. We conclude that lenders are unlikely to restrict credit for alert filers and that performance differences are not significant once removal from prescreened offers expires.

#### **8.4 Persistent Effects of Fraud Removal versus Persistent Behavioral Effects**

Is it possible the long-run effects we measure are simply the result of a one-time change due to the credit bureau's corrections of fraudulent and/or erroneous credit report information?

Because FACTA requires the credit bureaus to block any negative fraud-related activities after consumers identify and report them, the reduction in negative data and the increase in Risk Score would be a direct, "mechanical" effect of the fraud removal. These mechanical effects on Risk Score have been documented widely in the consumer finance literature (e.g., the impact of "bankruptcy flag" removal from consumers' credit reports can lead to increases of 10 to 16 points (Musto, 2004; Gross, Notowidigdo, and Wang, 2016; Dobbie, Goldsmith-Pinkham, Mahoney, and Song, 2016)).

We believe that the initial 12 point increase in Risk Scores we observe in panel D of Figure 3 is primarily attributable to the mechanical effect of fraud removal.<sup>16</sup> However, we argue that behavioral changes would be required for consumers to maintain this initial Score increase in the long term. It is important to note that Risk Scores are not simply stock variables that shift higher absent negative information but represent complex and dynamic measures that fluctuate because of changes in both stock and flow attributes, many of which are under the consumer's control (Avery, Calem, Canner, and Bostic, 2003). For example, Dobbie et al. (2016) find that, while consumers experience a 10 point score increase within the first year of a bankruptcy flag removal, the effect drops to 3 points by the end of year three. Therefore, it is not automatic that consumers would maintain their Score increase by correcting fraudulent information. Instead, consumers must pay attention to their credit files or borrow more carefully to maintain Risk Score gains. Our evidence from Figures 4 and 5 supports this conjecture because consumers have more accounts in good standing, fewer accounts in third-party collections, and other positive developments in The Long Run after identity theft; none of these long-term changes are likely to be mechanical.

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<sup>16</sup> Our result is consistent with other empirical research that has examined the effect of correcting or blocking credit file information. As mentioned previously, the 2012 Federal Trade Commission study found that correction of "material errors" led to an increase of 10 credit score points in 9 percent of the cases. Gross, Notowidigdo, and Wang (2016) find a slightly higher increase for bankruptcy flag removal of 14 points.

### 8.5 Wealth Effects

Individuals might be incentivized to monitor their credit reports because they experience material losses due to identity theft. If victims are less wealthy because of identity theft, perhaps due to unreimbursed personal losses, the marginal value of a dollar of credit may rise as consumers use the debt channel to smooth consumption. We argue that wealth effects are unlikely to explain all the results presented thus far. Results from the NCVS indicate that, while identity theft victims, on average, experience a gross financial loss of approximately \$2,200, only 14 percent of respondents experienced net personal out-of-pocket losses of \$1 or more. Of those individuals who experienced personal out-of-pocket losses, about half reported that the loss was less than \$100 (Harrell, 2015). Thus, although identity theft is an important and significant crime for consumers, financial losses resulting from identity theft are mostly borne by financial institutions and not by consumers. Therefore, while identity theft may affect credit outcomes through the wealth channel, the prevalence and magnitude of the wealth loss is limited, suggesting that the effects of identity theft on credit outcomes are unlikely to be explained by wealth effects alone.

### 9. Heterogeneous Effects: Subprime versus Prime Consumers

To understand whether the effects of identity theft vary depending on the credit characteristics of the borrower, we study the effects of fraud on consumers with subprime Risk Scores compared with consumers with prime Risk Scores. We estimate the following model:

$$Y_{it} = \beta_0 + \sum_{e=-8}^{22} \beta_{1e} T_e + \sum_{e=-8}^{22} \beta_{2e} T_e \times 1_{sub} + \beta_3 1_{sub} + \delta_i + X_{it} \gamma + \varepsilon_{it}, \quad (2)$$

where  $1_{sub}$  is an indicator variable equal to 1 for consumers with Risk Scores less than or equal to 660 at event times  $-2$ ,  $-1$ , or  $0$  and compare them with consumers with Risk Scores above 660 in the same time period. We summarize the results of this exercise in Figure 6.

Panel A of Figure 6 shows that subprime consumers have more credit inquiries than prime consumers during Victimization, The Short Run, and The Long Run. However, panel A also shows that, in event time 0, prime and subprime consumers have the same number of inquiries, on average. This finding may imply that, at the time of fraud, the behavior of inquiries for both groups is driven by common factors such as criminals applying for credit using stolen consumer information, which strengthens our argument that most of credit inquiries at the time of fraud are generated by criminals, not consumers.

Panel B of Figure 6 also shows that the effect of fraud on Risk Scores of subprime consumers is much larger than the comparable effect on Risk Scores of prime consumers. In particular, in event

time 1, the change in the average Risk Score for the subprime population is 18 points higher than the change in the Score for the prime population. There are three possible interpretations that are not mutually exclusive. First, this finding may be evidence that subprime consumers exhibit relatively more inattention prior to the fraud. Second, these consumers may have been exposed to more severe forms of fraud (see an increase in new accounts in panel D of Figure 6). Third, there may have been more errors unrelated to the fraud on the credit reports of these consumers. Separately, it is also worth noting that increases in Risk Scores for the subprime population persist in The Short Run and The Long Run.

Panel C of Figure 6 suggests that there are few differences between prime and subprime fraud victims in reverse address changes. Finally, panel D of this figure shows that subprime consumers have more new accounts opened during Victimization compared with prime victims. In addition, after identity theft, these consumers seem to continue opening a larger number of new accounts compared with prime borrowers. It is likely that subprime consumers face a different trade-off between the benefits of access to additional credit (these consumers are more likely to be credit constrained) and the potential cost of additional identity theft associated with more open accounts.

## **10. Robustness Checks**

### **10.1 Initial Fraud Alert Filers as a Control Group**

Because extended alert filers must go through an extensive process to file a police report and subsequently file an alert, there may be questions regarding the generalizability of our results to other groups. As mentioned previously, we do not compare filers to nonfilers because of potential concerns about selection bias. However, in addition to filing extended fraud alerts, consumers can also request an initial fraud alert. The major difference between an extended fraud alert and an initial fraud alert is that initial alerts do not require police reports or evidence of fraud.<sup>17</sup> Therefore, initial fraud alerts may be filed out of precaution or suspicion about possible identity theft or fraud. We argue that initial alert filers may be at least as motivated as extended fraud alert filers to request an alert but do not have the evidence of fraud that would allow them to

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<sup>17</sup> In addition, unlike extended fraud alerts, which are active for seven years, initial fraud alerts are only active for 90 days. However, consumers can renew initial fraud alerts in multiple and consecutive quarters. An initial fraud alert does not remove the consumer from lists used to make prescreened offers of credit, but it requires lenders to have additional policies and procedures in place to verify a consumer's identity when they receive a request to open a new account or other credit inquiries. For more details, see Cheney et al. (2014).



file an extended fraud alert. This difference between the two types of consumers filing initial and extended alerts provides us with a potential mechanism to separate the effects of fraud from unobserved factors that motivate the filing of a fraud alert by using initial alert filers as a control group for extended alert filers.

Empirically, we expand our sample to include both initial and extended alert filers and estimate an alternative specification of the regression model in Equation (1):

$$Y_{it} = \beta_0 + \sum_{e=-8}^{22} \beta_{1e} T_e + \sum_{e=-8}^{22} \beta_{2e} T_e \times 1_{ext} + \beta_3 1_{ext} + \delta_i + X_{it} \gamma + \varepsilon_{it}. \quad (3)$$

The only difference between this specification and the specification in Equation (1) is that we add a new indicator variable,  $1_{ext}$ , which is equal to 1 for extended alert filers and 0 for initial alert filers. We also interact this variable with event time indicators  $T_e$ . Thus,  $\beta_{2e}$  coefficients will capture the differences between initial and extended alert filers before and after they file an alert.<sup>18</sup>

Figure 7 presents results from comparing extended alert filers with initial alert filers. All results in this figure are qualitatively very similar to our main results in Figure 3. In particular, even after using initial alert filers to control for unobserved motivation in filing a fraud alert, we can see evidence of fraud among extended alert filers just before an alert, such as increased credit inquiries (panel A), decreased Risk Scores (panel B), more address reversals (panel C), and a higher number of new revolving accounts (panel D). The behavior of fraud victims after fraud is also similar to the main results with persistent increases in Risk Scores and fewer inquiries and new accounts opened by these consumers. Based on these results, we argue that our main findings are unlikely to be driven by the unobservable motivation of some fraud victims to file an alert and rather that these results are more likely to be due to the effect of actual victimization of consumers.

## 10.2 Controlling for Long-Term Event Time Trends

As can be seen in Figure 1, some credit variables, such as Risk Score, may have long-term trends in event time. These long-term trends may be explained by mean reversion in Risk Score and other variables. For example, Risk Scores of a group of subprime individuals may rise over time simply because the effects of adverse past events, which decreased their Scores in the first place, receive less weight in their current Score.

To separate the effect of mean reversion in credit variables from the longer-term effects of fraud, we estimate the following parametric model adopted from Dobkin et al. (2016):

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<sup>18</sup> Recall that, in Section 6.2, we estimated the specification in Equation (1) on the sample of extended fraud alert filers only. The results in this section include extended and initial alert filers as potential controls.

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

In this specification,  $e$  denotes fraud event time (which varies 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, Figures 3 through 5 show evidence of fraud shortly before alert filing and a discontinuous change in credit attributes at the time of 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.<sup>19</sup> While the specification in Equation (4) does not allow for individual specific trends in event time, we relax this constraint in Appendix Section A.1. Overall, our results are very similar with and without individual specific trends.

Table 2 summarizes results from our estimation of Equation (4). The coefficients on the event time variable in this table reveal the presence of trends independent of the treatment (victimization) in some credit variables. For instance, on average, the incidence of derogatory events decreases by 0.007 every quarter. Even after controlling for these long-run trends in these variables, we find generally negative effects of fraud on credit attributes on impact. The magnitudes of these effects are similar to our results in Figures 3 through 5. During fraud ( $-4 \leq e \leq -1$ ), we observe decreases in Risk Score of 5 points; increases in credit inquiries by 0.4; and increases in address reversals, new revolving accounts, and derogatory events.

We also find generally positive changes in credit variables after fraud, even after taking into account long-term trends in the variables. For the time after alert filing ( $e \geq 0$ ), Risk Scores increase by 11 points, the probability of having a collection decreases by 8 percentage points, and the proportion of cards in good standing rises by 2.4 percentage points. Similar to our earlier results, inquiries and reverse address changes are elevated after fraud, while cards with positive balances decrease. 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

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<sup>19</sup> 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.

indicate that about 5 points of the initial jump in the Risk Score dissipate 10 quarters after the fraud event. Overall, these results are very similar to our main results obtained without controlling for long-term event time trends.

## **11. 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 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 most likely identity theft victims because this type of fraud alert requires them to file a police report (with accompanying evidence of identity theft and penalties for misrepresenting this information). The nature of the extended fraud alert filing system and our data provide us with unique advantages relative to other studies of consumer financial fraud. In particular, given the high burden of proof necessary to file an alert, our analysis is highly unlikely to suffer from Type I errors, providing strong internal validity for our results.

Our results show that, during Victimization, identity theft decreases the average Risk Scores of victims and increases new (likely fraudulent) accounts, inquiries, and instances of reverse address changes relative to the control group. The negative effects stemming directly from identity theft generally persist between one and two quarters. In The Long Run, Risk Scores of fraud victims rise by an average of 12 points, increasing the proportion of fraud victims with prime 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 the fraud. In both The Short Run and The Long Run periods, we also find that victims have more cards in good standing and a lower average incidence of derogatory events. The persistence of the reduction in the incidence of major derogatory and third-party collection events is particularly striking. However, despite these improvements, it does not appear that most victims take advantage of their improved financial standing to seek or obtain additional credit. Instead, for most victims, we observe a (selective) decreased attachment to the credit card market, with consumers opening fewer new credit cards and holding fewer active revolving accounts overall. The exception occurs among *some* subprime consumers who use their higher Risk Scores to apply for and obtain additional credit cards. Of course, those consumers face a different trade-off between the risk of experiencing more fraud and the ability to relax credit constraints.

Our empirical results provide robust evidence that allow us to evaluate the plausibility of a number of potential drivers for the identified effects and their persistence. In particular, we argue

that limited attention and changes in consumer trust may play important roles in explaining the behavior of identity theft victims. The asymmetric positive impact on key credit variables in The Short Run, where credit performance improved by more than it deteriorated, suggests that consumers were not focused on their credit reports prior to victimization. The persistent improvement over time to consumer credit attributes, coupled with evidence of selective detachment from the credit card market (consumers maintaining fewer open bankcards and carrying balances on fewer of them, yet maintaining similar total balances across cards), suggests at least two conclusions. First, consumers may be paying increased attention to their credit and credit reports for a substantial period after identity theft. Second, many consumers do not seem to take advantage of the improvement in their apparent financial health and instead reduce their presence in the credit card market. To the extent that identity theft reduces trust in electronic forms of credit and payments, such a negative shock can have spillover effects that influence consumer decision-making in material ways.

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**Table 1. Summary Statistics**

Variable	Nonfilers		Filers			
	Mean	S.D.	<u>At t = -4:</u>		<u>At t = 0:</u>	
			Mean	S.D.	Mean	S.D.
Number of inquiries, past 3 months	0.540	0.989	1.028	1.646	1.553	2.159
Address reversals in the last quarter	0.005	0.070	0.011	0.102	0.020	0.142
Number of revolving accounts opened within 6 months	0.239	0.589	0.342	0.757	0.390	0.834
Risk Score	695.107	108.184	641.341	118.999	654.398	109.136
Prime indicator variable (1 if Risk Score 660 or less)	0.664	0.473	0.446	0.497	0.486	0.500
Total revolving credit limit	36,435.9	66,544.4	40,554.1	89,808.5	37,257.8	86,904.4
Total revolving balance	11,358.8	38,696.9	13,633.1	49,283.7	12,890.3	46,564.9
Number of bankcards in good standing	0.880	0.308	0.795	0.380	0.813	0.362
Number of bankcard accounts w/ update w/in 3 months w/ balance >0	1.600	1.459	1.811	1.569	1.736	1.550
Number of open bankcards	2.050	2.090	2.118	2.343	2.179	2.269
Incidence of third-party collections	0.144	0.351	0.284	0.451	0.200	0.400
Incidence of major derogatory events	0.066	0.249	0.145	0.352	0.118	0.323
Number of Observations	23,038,801		39,723		52,649	

Notes: Risk Score is the Equifax Risk Score. The nonfilers statistics are based on data from a 10 percent sample of all nonfilers in the CCP. The numbers of observations shown represent the largest number of observations among all variables (some variables have fewer observations because of missing values).

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

**Table 2. The Effect of Fraud on Credit Variables After Controlling for Event Time Trends**

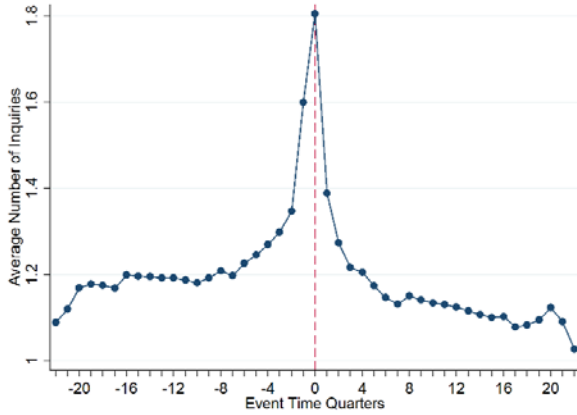
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Risk Score	Inquiries	Address Reversals	New Revolving Accounts	% Cards in Good Standing	Cards with Positive Balances	Open Cards	Collections	Derogatory Events
Time	0.318 (0.547)	-0.004 (0.015)	0.001 (0.001)	0.004 (0.008)	0.002 (0.002)	0.019 (0.013)	-0.005 (0.014)	0.004 (0.003)	-0.007** (0.003)
Time <sup>2</sup>	0.005 (0.008)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	-0.000*** (0.000)
1(Time≥0)	11.441*** (0.933)	0.299*** (0.023)	0.011*** (0.001)	0.003 (0.012)	0.024*** (0.005)	-0.081*** (0.020)	-0.078*** (0.022)	-0.082*** (0.006)	-0.005 (0.006)
1(Time≥0)×Time	-0.464** (0.195)	-0.093*** (0.004)	-0.002*** (0.000)	-0.021*** (0.002)	-0.003*** (0.001)	0.006 (0.004)	-0.017*** (0.005)	0.002* (0.001)	0.006*** (0.001)
1(Time≥0)×Time <sup>2</sup>	0.012 (0.008)	0.003*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)
1(-4≤Times-1)	-5.104*** (0.922)	0.383*** (0.025)	0.005*** (0.001)	0.105*** (0.012)	-0.003 (0.005)	0.058*** (0.020)	0.048** (0.022)	-0.019*** (0.006)	0.034*** (0.006)
1(-4≤Times-1)×Time	-1.350*** (0.185)	0.101*** (0.005)	0.001*** (0.000)	0.026*** (0.003)	-0.000 (0.001)	0.014*** (0.004)	0.011*** (0.004)	-0.004*** (0.001)	0.008*** (0.001)
Constant	391.421*** (44.924)	2.022** (0.846)	0.010 (0.049)	4.115*** (0.441)	1.217*** (0.255)	2.716*** (0.978)	-3.085** (1.243)	-0.804*** (0.210)	0.916*** (0.237)
Observations	1,177,155	1,030,055	1,197,160	1,097,608	830,411	856,926	1,042,287	1,197,160	1,197,160
R-squared	0.040	0.024	0.004	0.019	0.011	0.020	0.082	0.007	0.014

Notes: This table shows the effect of fraud 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. \*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10% levels, respectively. Risk Score is the Equifax Risk Score.

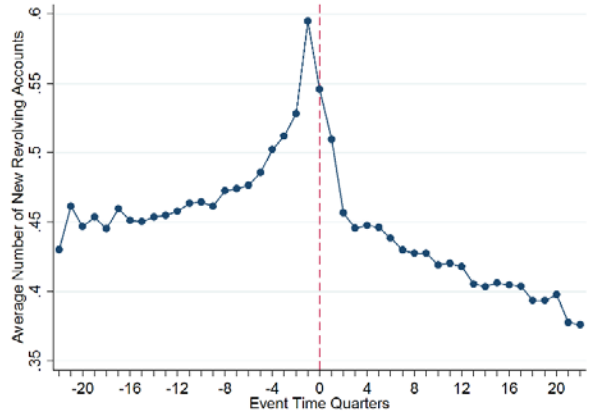
Sources: Authors' calculations using data from FRBNY/Equifax Consumer Credit Panel, augmented with variables obtained by the Consumer Finance Institute from Equifax

**Figure 1. Indicators of Potential Identity Theft in Event Time**

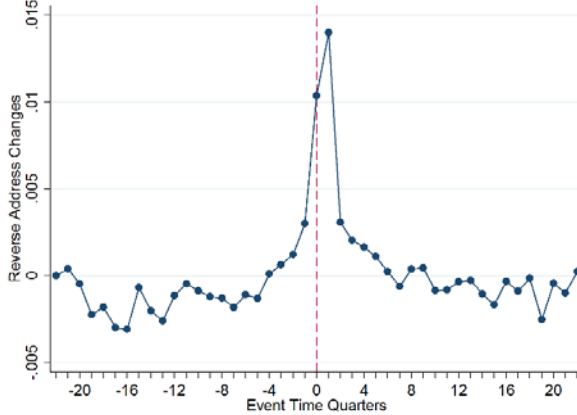
Panel A. Credit Inquiries



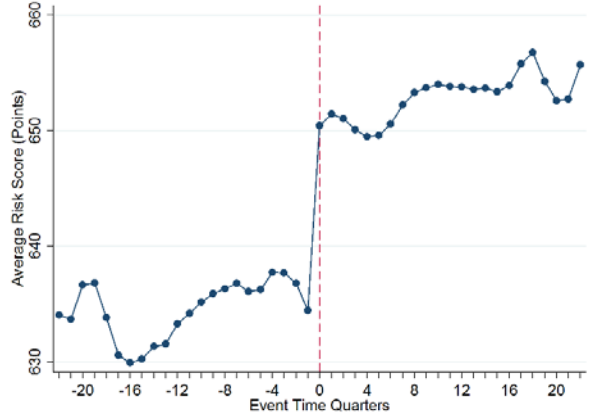
Panel B. New Revolving Accounts



Panel C. Address Reversals



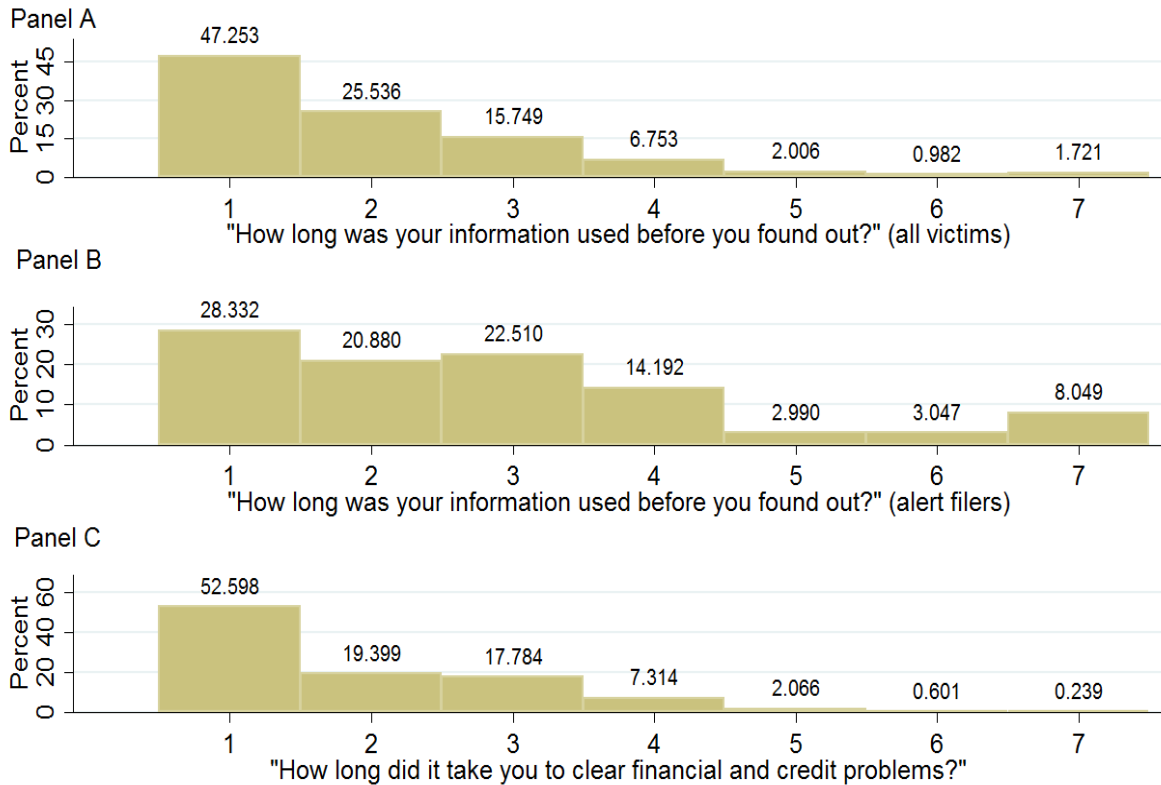
Panel D. Risk Score



Notes: This figure depicts average values of credit bureau characteristics of fraud victims before and after fraud activity. 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. The data include only extended fraud alert filers in Q1:2008–Q3:2013. The effect of the business cycle is removed using calendar time dummies. Risk Score is the Equifax Risk Score.

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

**Figure 2. Speed of Discovery and Clearing Up Identity Theft**

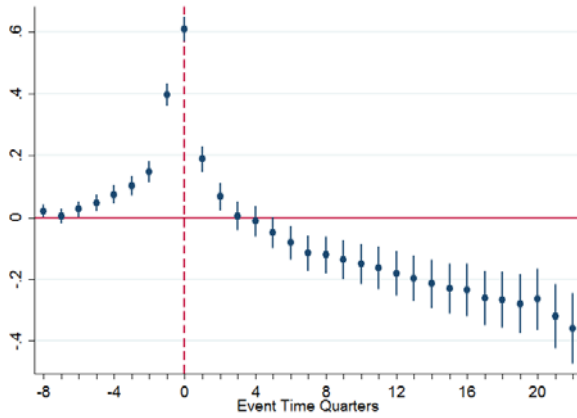


1 One day or less	4 One month to less than three months	7 One year or more
2 More than a day, but less than a week	5 Three months to less than six months	
3 At least a week, but less than a month	6 Six months to less than one year	

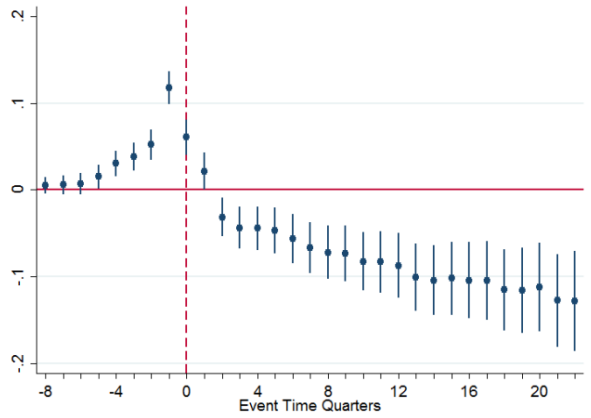
Notes: Survey responses from the Bureau of Justice Statistics' National Crime Victimization Survey 2012 Identity Theft Supplement. Panel A (total number of observations of 3,879): Percent of all identity theft victims who discovered fraud less than three months after its occurrence is 95.3 percent. Panel B (total number of observations of 236): Percent of identity theft alert filers who discovered fraud less than three months after its occurrence is 85.9 percent. Panel C (total number of observations of 3,777): Percent of all identity theft victims reporting that clearing up financial and credit problems took less than three months is 97.09 percent.

**Figure 3. Indicators of Potential Identity Theft – Treatment versus Control**

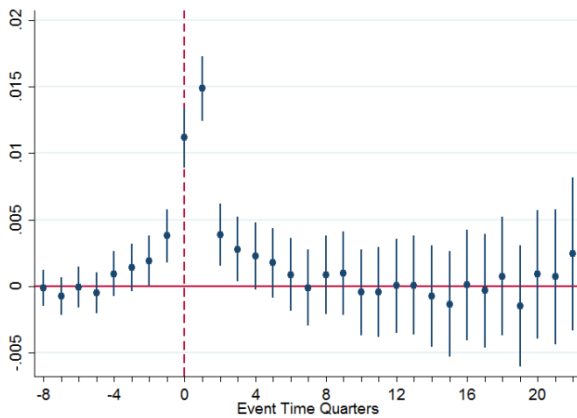
Panel A. Credit Inquiries



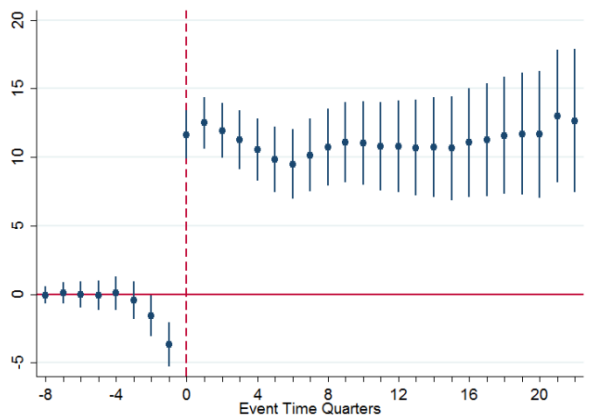
Panel B. New Revolving Accounts



Panel C. Address Reversals



Panel D. Risk Score

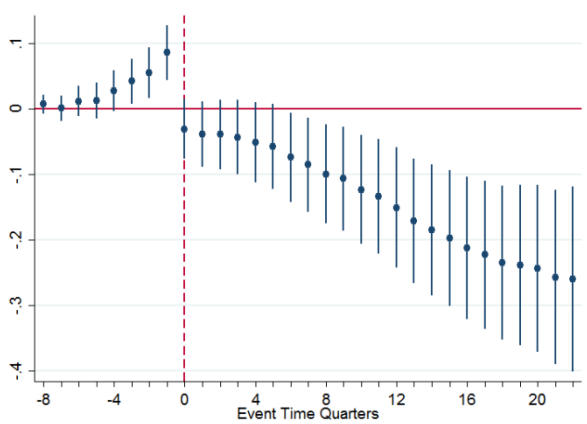


Notes: This figure depicts differences in the credit bureau characteristics of fraud victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All quarter dummies prior to quarter -8 are omitted. The dots represent point estimates, and bands show 95% confidence intervals. The data include only fraud alert filers in Q1:2008–Q3:2013. The identification comes from the exogenous timing of fraud activity. Risk Score is the Equifax Risk Score.

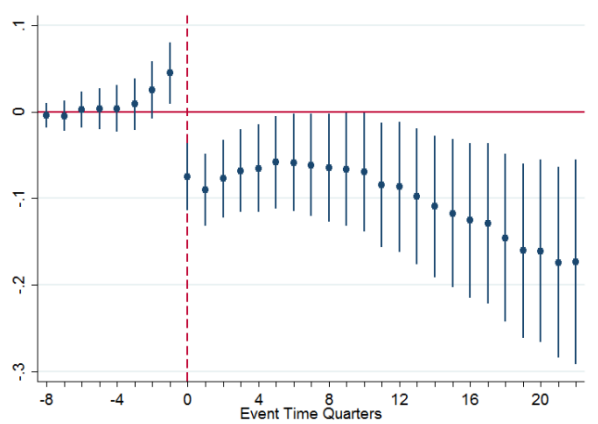
Sources: Authors' calculations using data from FRBNY/Equifax Consumer Credit Panel, augmented with variables obtained by the Consumer Finance Institute from Equifax

**Figure 4. The Effect of Fraud on the Number of Open Cards, Cards with Balances, Age of Newest Card, and Total Revolving Credit Limit**

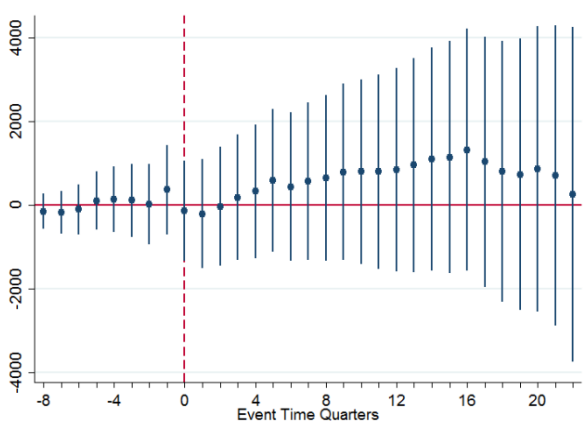
Panel A. Open Bankcards



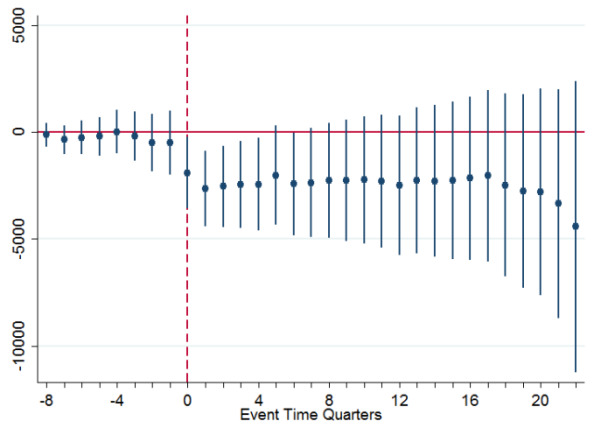
Panel B. Cards with Positive Balances



Panel C. Total Revolving Balance



Panel D. Total Revolving Credit Limit

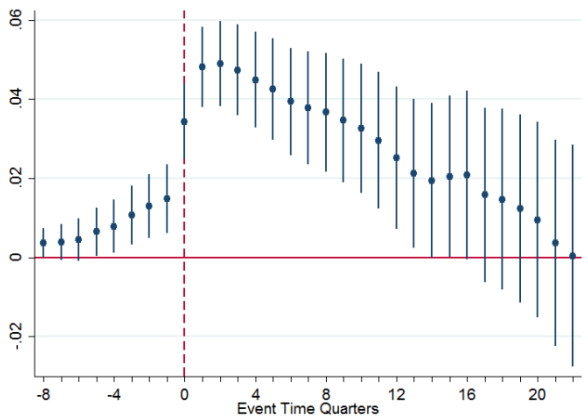


Notes: This figure depicts differences in the credit bureau characteristics of fraud victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All quarter dummies prior to quarter -8 are omitted. The dots represent point estimates, and bands show 95% confidence intervals. The data include only fraud alert filers in Q1:2008-Q3:2013. The identification comes from the exogenous timing of fraud activity.

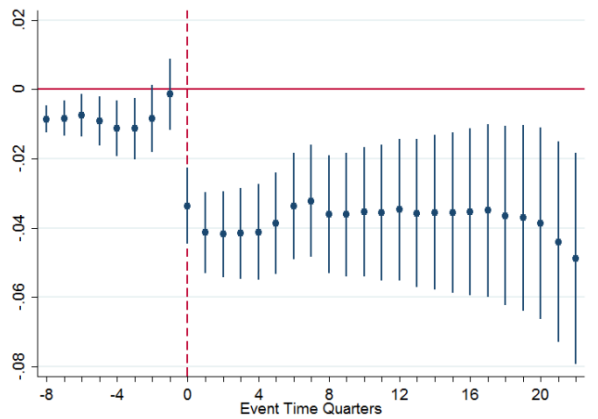
Sources: Authors' calculations using data from FRBNY/Equifax Consumer Credit Panel, augmented with variables obtained by the Consumer Finance Institute from Equifax

**Figure 5. The Effect of Fraud on the Proportion of Cards in Good Standing, the Incidence of Major Derogatory Events, and Third-Party Collections**

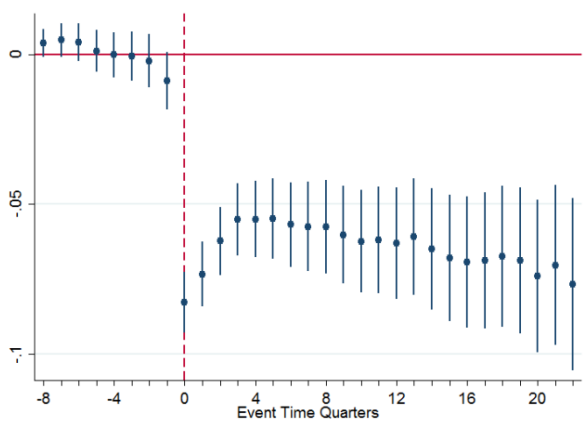
Panel A. Cards in Good Standing



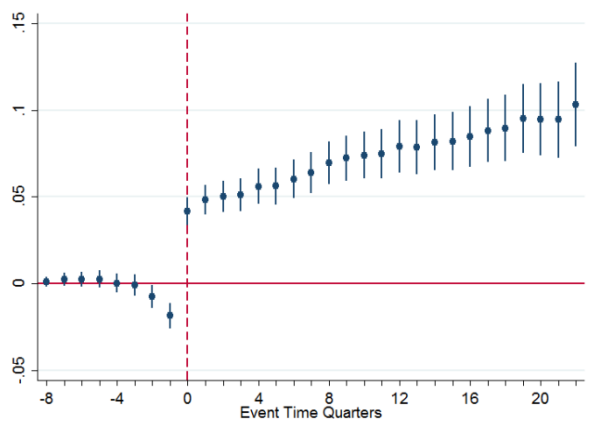
Panel B. Major Derogatory Events



Panel C. Third-Party Collections



Panel D. Share of Prime Consumers

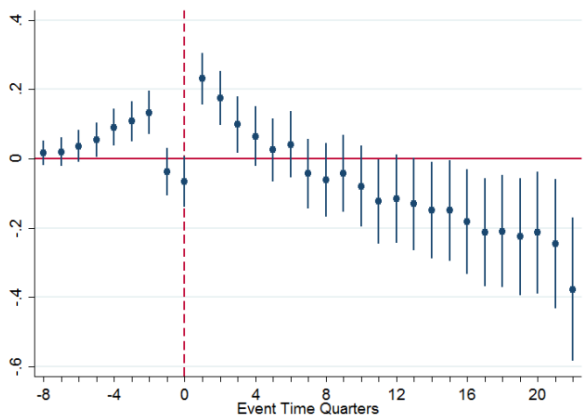


Notes: This figure depicts changes in the credit bureau characteristics of fraud victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies. Prime is defined as having a Risk Score greater than 660. Time 0 denotes the quarter of fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. All quarter dummies prior to quarter -8 are omitted. The dots represent point estimates, and bands show 95% confidence intervals. The data include only fraud alert filers in Q1:2008–Q3:2013. The identification comes from the exogenous timing of fraud activity.

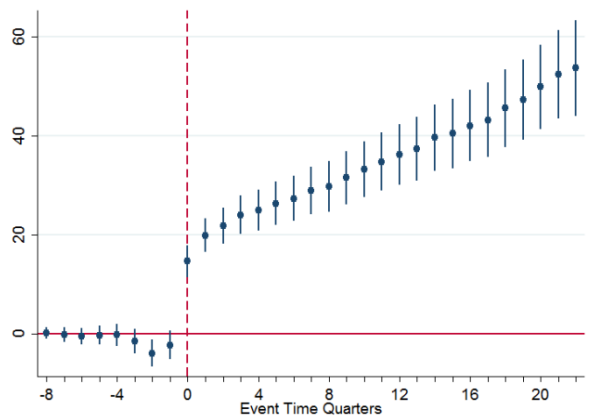
Sources: Authors' calculations using data from FRBNY/Equifax Consumer Credit Panel, augmented with variables obtained by the Consumer Finance Institute from Equifax

**Figure 6. The Effect of Fraud on Consumers with Subprime Risk Scores Compared with Consumers with Prime Risk Scores**

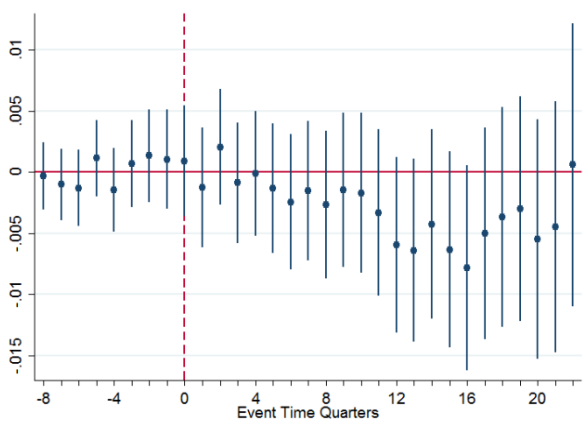
Panel A. Credit Inquiries



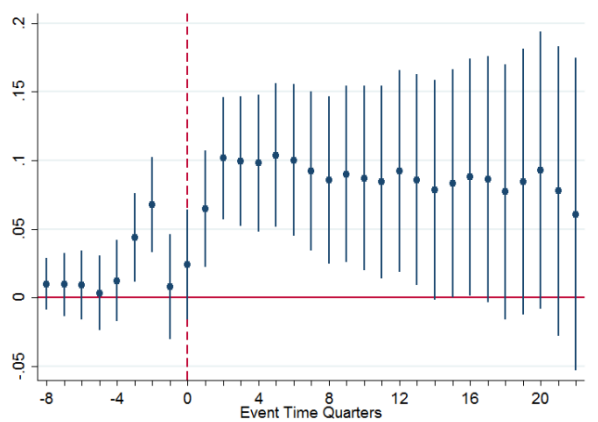
Panel B. Risk Score



Panel C. Address Reversals



Panel D. New Accounts



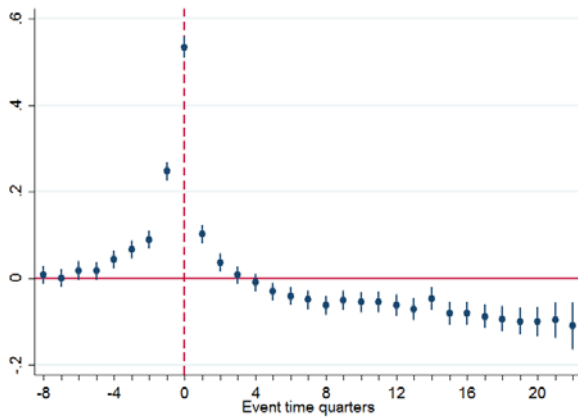
Notes: This figure depicts changes in the credit bureau characteristics of subprime (less than or equal to 660) and prime (more than 660) fraud victims at the time of fraud alert and the two quarters before that. These changes are estimated based on a distributed lag specification with event time dummies interacted with the subprime/prime indicator. 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 quarter dummies prior to quarter -8 are omitted. The dots represent point estimates, and bands show 95% confidence intervals. Risk Score is the Equifax Risk Score.

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

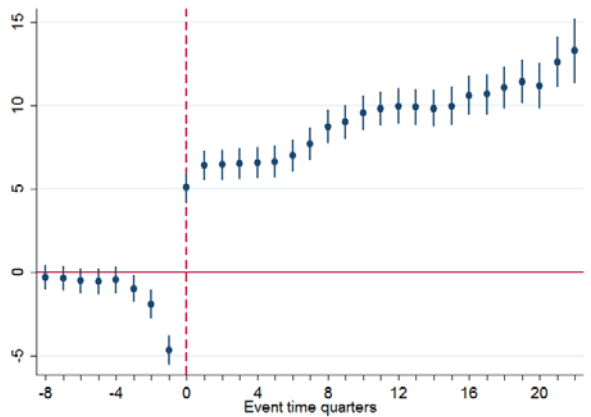


**Figure 7. The Effect of Fraud on Credit Bureau Variables Using Initial Alert Filers as Controls**

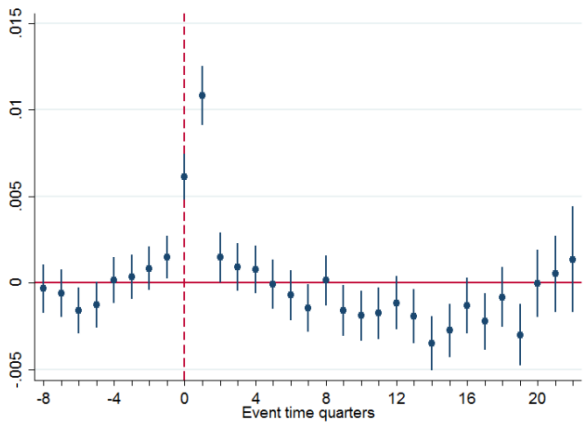
Panel A. Credit Inquiries



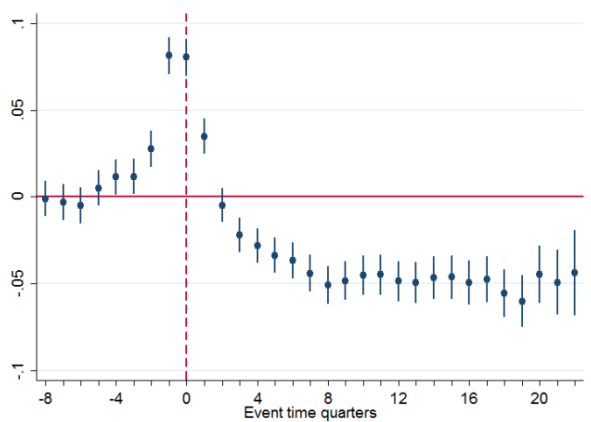
Panel B. Risk Score



Panel C. Address Reversals



Panel D. New Accounts



Notes: This figure depicts differences in the credit bureau characteristics of fraud victims before and after fraud activity. These changes are estimated based on a distributed lag specification with event time dummies interacted with the extended/initial alert indicator variable. 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 quarter dummies prior to quarter -8 are omitted. The dots represent point estimates, and bands show 95% confidence intervals. The treatment group includes extended fraud alert filers. The control group consists of initial fraud alert filers. Risk Score is the Equifax Risk Score.

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

## Appendix

### A.1 Controlling for Individual-Level Mean Reversion

The econometric model in Equation (4) 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 fraud 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 fraud, we specify a model similar to that of Musto (2004):

$$Y_{it} = \beta_0 + \delta_i + \delta_i \times t + \delta_i \times t^2 + \beta_1 D_{it} + \alpha_t + \varepsilon_{it}, \quad (5)$$

where  $\delta_i$  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.<sup>20</sup> 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 filing an extended fraud alert. 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. However, estimating individual fixed effects and individual quadratic time trends introduces computational restrictions. For each panel in Equation (5), we perform our analysis on a 6.7 percent random subsample of our data.

We present results of this analysis from Equation (5) for Risk Score, proportion of bankcards in good standing, and new revolving accounts in Appendix Table A1. The estimates are quantitatively similar to those previously reported in Figures 3 and 5. After controlling for individual fixed effects and individual mean reversion, we find that having an active extended fraud alert increases Risk Scores, on average, by 13.6 points; increases the proportion of cards in good standing by 1.8 percentage points; and decreases the number of new revolving accounts by 0.085. 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.

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<sup>20</sup> As mentioned in the previous sections, use of individual-level quadratic time trends is motivated by observed patterns in the data. Estimates using a linear time trend produce similar results.

## A.2 Heterogeneous Effects: Consumers with and Without Credit Inquiries

To understand whether the effects of identity theft vary depending on the credit characteristics of the borrower, we study the effects of fraud on consumers with credit inquiries during Victimization compared with consumers without credit inquiries. To compare the effects of fraud on consumers with and without inquiries, we estimate the following model:

$$Y_{it} = \beta_0 + \sum_{e=-8}^{22} \beta_{1e} T_e + \sum_{e=-8}^{22} \beta_{2e} T_e \times 1_{inq} + \beta_3 1_{inq} + \delta_i + X_{it} \gamma + \varepsilon_{it}, \quad (6)$$

where  $1_{inq}$  is an indicator variable equal to 1 for consumers with credit inquiries in either the two quarters preceding alert filing or in the quarter of alert filing (event time  $-2$ ,  $-1$ , and  $0$ ).

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 cannot clearly distinguish between these two types of inquiries in our data. However, we can compare fraud victims without inquiries with fraud victims with inquiries. We hypothesize that consumers without inquiries may be (1) less attached to the credit market and less attentive to their credit information, and (2) subject to existing account fraud or other fraud that does not result in credit inquiries.

Figure A2 shows changes in credit variables of fraud victims without credit inquiries at time  $-2$ ,  $-1$ , or  $0$  compared with consumers with credit inquiries in that time period. The decline in credit inquiries at the time of fraud shown in panel A of Figure A2 is mechanical, but the other results are not. Panel B of this figure suggests that no-inquiry fraud victims experience larger effects of fraud on Risk Scores in The Short Run. This might suggest that this subgroup of consumers exhibited more inattention before the fraud than the victim population as a whole.

Panel C of Figure A2 suggests that there is no statistically significant difference in terms of reverse address changes between fraud victims with and without inquiries. However, panel D of this figure shows that victims with inquiries are more likely to have new accounts opened during time  $0$ . This result is consistent with criminals being successful in applying for credit with stolen consumer information for a fraction of the population with credit inquiries or a valid consumer acquiring new credit.

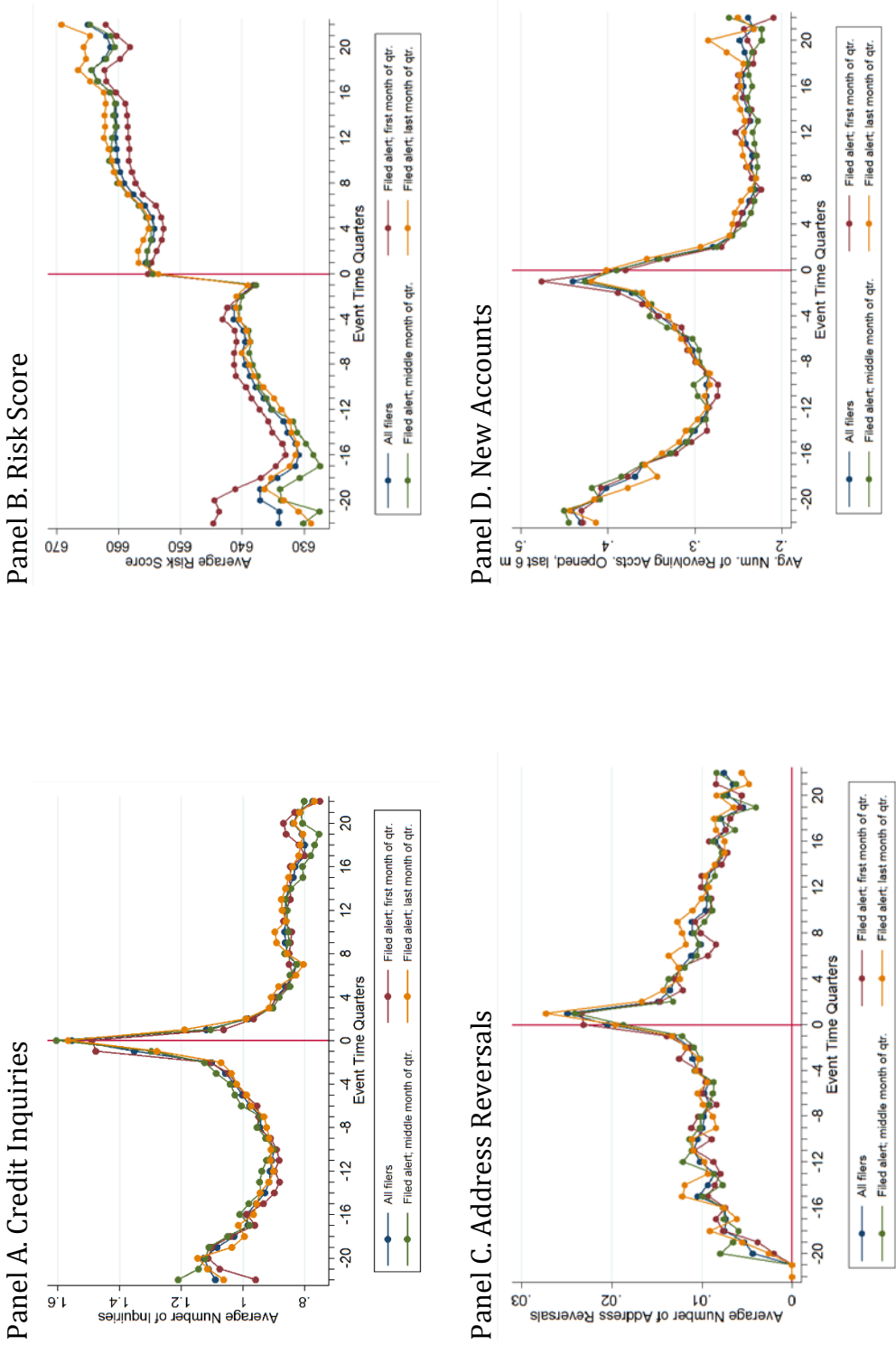
**Table A1. The Effect of Fraud on Credit Variables, Controlling for Individual Mean Reversion**

	(1)	(2)	(3)
	Risk Score	Cards in Good Standing	New Revolving Accounts
After extended alert filed	13.606*** (1.238)	0.018*** (0.006)	-0.085*** (0.019)
Number of panels	3,520	3,234	3,438
Total observations	79,715	55,995	74,179
Within $R^2$	0.553	0.565	0.317
Overall $R^2$	0.929	0.844	0.446

Notes: All specifications include individual fixed effects, individual quadratic time trends, and time fixed effects. Standard errors are clustered at the individual level. Risk Score is the Equifax Risk Score.

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

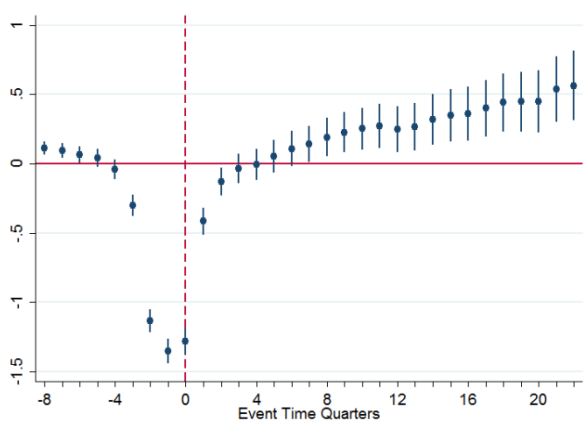
**Figure A1. The Effect of Fraud on Credit Bureau Variables by Month of Alert Filing**



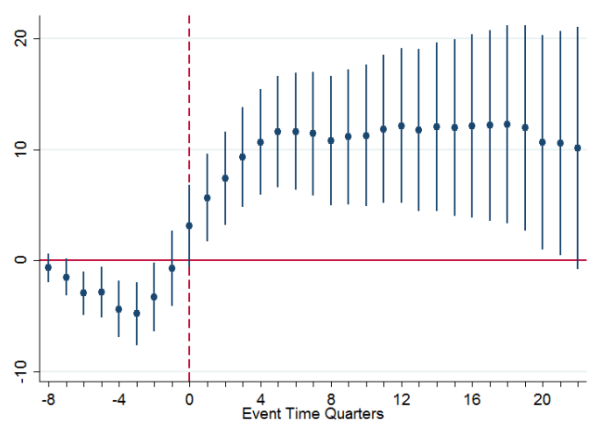
Notes: This figure depicts the average values of the credit bureau characteristics of fraud victims before and after fraud activity by the month of the extended alert filing. Time 0 denotes the quarter of extended fraud alert filing, with negative time being quarters before this event and positive time being quarters after the event. Risk Score is the Equifax Risk Score. Sources: Authors' calculations using data from FRBNY/Equifax Consumer Credit Panel, augmented with variables obtained by the Consumer Finance Institute from Equifax

**Figure A2. The Effect of Fraud on Consumers Without Credit Inquiries Compared with Consumers with Credit Inquiries**

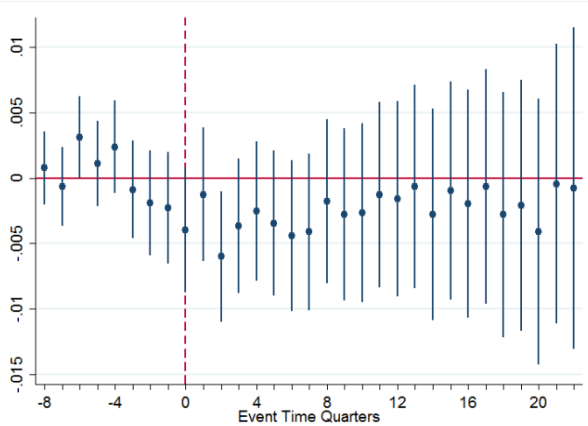
Panel A. Credit Inquiries



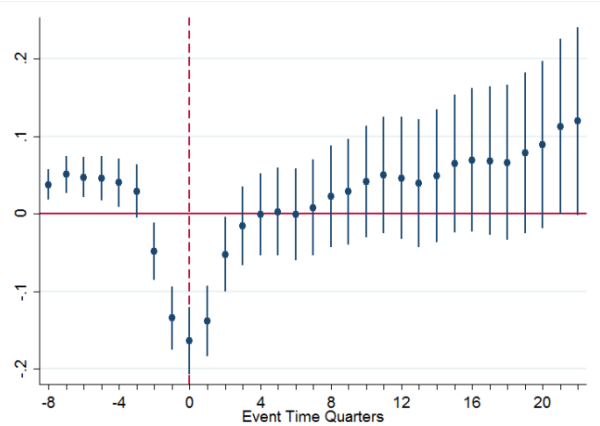
Panel B. Risk Score



Panel C. Address Reversals



Panel D. New Accounts



Notes: This figure depicts changes in the credit bureau characteristics of fraud victims without credit inquiries at the time of fraud alert and the two quarters before that relative to credit bureau variables of fraud victims with credit inquiries in the same period. These changes are estimated based on a distributed lag specification with event time dummies interacted with the no inquiry/inquiry indicator. 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. These figures imply that less attentive consumers who were not shopping for credit before fraud (or who had no new account fraud) have larger increases in Risk Score than more attentive consumers (who were shopping for credit). All quarter dummies prior to quarter -8 are omitted. The dots represent point estimates, and bands show 95% confidence intervals. Risk Score is the Equifax Risk Score.

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