House of Stolen Cards: Does Payment Security Improve Credit Outcomes for Households?

Draft version: March, 2025

Abstract

Credit card fraud is the most common type of identity fraud in the U.S. with a cost of over $11.64 billion. In 2014, the U.S. government pushed for widespread adoption of more secure chip-enabled credit cards to safeguard consumers from financial fraud and improve confidence in the marketplace. We study the effects of this technological innovation in payment security on household credit outcomes. Using a matched sample staggered difference-in-differences event study, we show that before this intervention fraud exposed consumers faced decline in access to credit. Post this innovation, consumers see greater credit availability. We then examine consumer behavior associated with exposure to fraud and find that consumers reduce their credit demand and face increased financial distress. These findings do not change following the innovation. Heterogeneity analysis shows that low credit score households are more likely to have higher decline in credit demand and increased financial distress. Our findings suggest that persistent consumer distrust underscores the need for further policy innovations, such as one-time passcodes for credit card transactions and sufficient financial education to consumers.

Keywords: Payment Security, Consumer Credit, Fraud Risk, Credit Card, Lending, Credit Information, Household Finance.
JEL Classification: G21, G28, G50, G51, G53.

1 Introduction

Credit cards are arguably the most widely used financial instrument in the United States. More than 80% of U.S. adults have a credit card and over 70% of all retail spending was processed using credit cards (CapitalOne, 2022; Fed, 2022). This ubiquity also extends to identity theft with credit card fraud being the most common form, with a cost of over $11.64 billion[1] (FTC, 2023; Nilson, 2023). In 2014, the Obama administration introduced the BuySecure initiative which aggressively pushed for widespread adoption of more secure chip enabled credit cards by both lenders and merchants. This initiative was aimed to protect consumers from financial fraud and improve confidence in marketplace.

Consumers who are exposed to fraud are faced with a shock to trust in financial institutions (McKinsey, 2020). The lender failed to prevent unauthorized transactions, this results in consumers developing less trust in the lender's security practices.[2] Brenner et al. (2020) find that following instances of fraud, consumers have lower confidence in financial matters. The lenders need to balance managing risk associated with the fraudulent event and the revenue generated from interchange fees of these consumers. How financial fraud affects fraud exposed households is unclear.

In this paper, we empirically examine how payment security affects credit outcomes for the households who experience financial fraud. Using micro-data on consumer credit records from a major credit bureau in the U.S., we identify consumers exposed to credit card fraud. We then examine how technological innovation in payment security affects household's access to credit and their response upon exposure to fraud. We study the plausibly exogenous roll out of chip-enabled credit cards in the U.S. market in 2014. Following aggressive prompting

[1] Fair Credit Billing Act (1974) reduces the consumer liability, in case of unauthorized transactions, to $50 and rest is borne by lenders or merchants. See Section 2 for more details.

[2] McKinsey (2020) find that following a bad experience with fraud resolution, consumers are more likely to close their accounts.

and organizing by the Obama administration, adoption of these cards became widespread in the U.S. credit market under the BuySecure initiative. This innovation reduced the instances of fraud by 78%.[3]

In our empirical strategy, we use detailed information from Gies Consumer Credit Panel (GCCP) on credit line level data, available at an annual frequency for a random sample of about 1% of the U.S. population with a credit report from a major U.S. credit bureau. We use a matched sample staggered difference-in-differences event study design to examine credit outcomes when a consumer first experiences credit card fraud. Our matched sample is constructed using characteristics such as credit limit, account balance, credit score, income, year, and state of residence to compare the outcomes for consumers who experienced fraud relative to control consumers who never experience a credit card fraud. Our main specification employs triple difference-in-differences to investigate credit outcomes for fraud exposed households, with and without more secure payment technology. We include matched group by calendar year fixed effects to control for time-varying unobserved heterogeneity across groups. We also include individual by group fixed effect to remove the time-invariant heterogeneity among individuals across groups. To investigate heterogeneous impact and response by households we split the consumers into high credit score and low credit score sub-samples.

We obtain three key sets of results. First, we find that consumers who experience fraud prior to the technology innovation face a reduction in credit access. After the innovation in payment security, consumers see an improvement in availability of credit. In our triple difference, we see that post the fraudulent event, the consumers who experience the event with the technology shock have a higher total credit limit. This increase in total credit limit is economically significant with an average increase of $3,071 (7.6% relative to mean). Additionally, the consumers in the prior treated event-cohorts, i.e. consumers with fraudulent event year prior to 2014, experience a sudden jump in their total credit limit in 2014. These results suggest that enhanced payment security is associated with a greater availability of

[3]This was followed by a shift in cost of fraud liability from the lenders onto the merchants. See Section 2 for a more detailed discussion on the payment security technology and liability shift.

credit for the households.

Second, we find that after a fraudulent experience consumers restrict their demand for credit. Relative to their matched peers, consumers who experience credit card fraud have a higher number of new credit cards and credit card inquiries prior to experiencing the fraudulent event. However, after the fraudulent event consumers inquire less and open fewer new accounts. This decline in demand is observed despite enhanced payment security after the BuySecure initiative. This suggests that consumers are experiencing a shock to trust that is not attenuated with the introduction of more secure payment technology.

Finally, heterogeneity analysis shows that low credit score consumers are more likely to face higher reduction in credit demand and increased likelihood of financial distress post exposure to fraud. Since low credit score consumers are associated with low income and less financial sophistication, these results suggests that low income consumers are experiencing a greater shock to trust in payment security. These results suggest that the BuySecure initiative did not achieve it's intended goal of improving consumer confidence.

Overall, our results provide evidence on the importance of payment security in preserving access to credit for consumers. The introduction of more secure cards is associated with a dramatic reduction in the probability of fraudulent events and an increase in credit supply. However, even with improved security, consumers are unwilling to seek more credit with low credit consumers being impacted more. Our findings suggest that while achieving the goal of reducing fraud, the BuySecure initiative did not succeed in improving consumer confidence. This persistent consumer distrust on financial institutions underscores the need for further policy innovations, such as one-time passcodes and sufficient financial education to consumers.

We are the first to investigate credit outcomes for consumers who have experienced these fraudulent events. To the best of our knowledge, no one prior has examined how these credit card frauds are associated with the equilibrium credit outcomes. We are also the first ones to study the technology shock of introduction of chip-enabled cards in the US credit markets through the BuySecure initiative.

Our work relates to the literature of consumer credit frauds. This literature is sparse, in part due to prior data unavailability and difficulty associated with the identification of fraud. Sullivan (2013) documented the impact of chip adoption on other countries' fraud rate and Hayashi (2019) examined the direct impact of the implementation and the technology on total fraud rates. We contribute our identification of frauds to this literature.

Our paper also contributes to the literature on payment security. Kahn et al. (2017) show that when a consumer's peer(s) perceives the security of a payment instrument as high, then the consumer's perceived security of that instrument also increases. Blascak and Toh (2022) show that when exposed to fraud, consumers with prior experience of fraud or identity theft are more likely to close their credit cards compared to the consumers with no prior experience of fraud or identity theft.

Then, our work is related to the literature on lenders and credit cards. Chava et al. (2023) show that lenders transmit their wholesale funding shocks to consumers by reducing their credit card limits. Agarwal et al. (2010) show that consumers spending and debt increases after introduction of credit card cashback programs by the lenders. Agarwal et al. (2018) looks at the adverse selection in credit cards market and find that more liquidity constrained individuals are more likely to respond to inferior solicitation by lenders and are more likely to default ex post.

Finally, our paper also adds to the literature on the role of credit reporting flags for credit extension. Dobbie et al. (2020) and Gross et al. (2021) use removal of credit reporting data to show that removal of lenderruptcy flags from the credit reports lead to a increase in credit limit and borrowing, and a reduction of credit card interest rates, respectively. Guttman-Kenney (2023) studies the natural disaster flag present on consumer credit reports and finds that the flag does not increase credit access.

The rest of the paper is as follows: Section 2 discusses credit card transactions, fraud liability, and the improved payment security technology. Section 3 describes the data used in our analysis. Section 4 provides the main empirical strategy to examine the credit outcomes and consumer response associated with fraudulent events. Section 5 concludes.

2 Background

2.1 Credit card transactions and fraud liability

In a typical credit card transaction, four parties are involved (see Figure A.1) in the payment process. First is the consumer who uses the credit card for making a payment. Second is the consumers' lender who underwrites the consumer by financing the transaction. The lender's fraud department is responsible for checking any suspicious transaction on the consumer's credit card. The third is the processor which provides the technology for the transaction to take place. Finally, there's a merchant who has the credit card terminal (point-of-sale machine) from the processor. The merchant need not have any formal relationship with the consumer's lender. When a consumer sees a fraudulent/unauthorized transaction on the credit card statement, the Fair Credit Billing Act (FCBA) of 1974, enables the consumer to raise a dispute on the credit card transaction. FCBA is a federal laws that requires the lenders to investigate the dispute and settle it within 90 days. During the investigation period the lender cannot collect the balance of the disputed transaction. The law also states that a fraudulent transaction dispute cannot impact a consumer's credit score. Under FCBA, for fraudulent transactions the card-holder's liability is limited to \$50. Further, many lenders offer a zero liability policy which reduces the consumer's liability to \$0 in case of credit card fraud.

Whereas, the merchant is not liable for card present transactions, if it follows the best practices such as using tap or chip processing instead of swiping the credit card to execute transaction. Further, the processor is responsible only for providing the technology for transaction execution. Therefore, in most cases, all the loses related to card present[4] fraudulent

[4]For card not present fraudulent transactions, which are more common in e-commerce, the liability is

transactions are to be borne by the lender. The consumer gets a replacement card with a new number, the credit history associated with the card remains the same. lenders also claim that the consumers' credit standing will not get impacted by the occurrence of the fraudulent transactions. For example; *"When you report your card as lost or stolen to the [lender], they will arrange for a new card to be sent to you. Replacing a credit card won't affect your credit score....the card account and the age of that account remain the same for the purpose of credit reporting." (Chase (2024))*

However, following a fraudulent event the consumer should be perceived as being more risky by the lender. For the lenders, the consumers with fraudulent charges are either not following the best practices to keep the credit cards details safe or it might be possible that the consumers are themselves fraudulently disputing the charges for the transactions they have made. In either case lender's cost for extending credit to these consumers has increased. On the other hand, lenders want these consumers to keep on using their credit cards which generates revenue for the lender.

2.2 Buy Secure Initiative & Liability Shift

Prior to 2014 credit cards in the US used a magnetic stripe to store the information required to execute transaction such as card number, security code, and owner's name. This stripe technology has been around since 1960's and stealing information from these stripe cards was easy. A common practice was to use skimmers which are illegal card readers that can copy and replicate the un-encrypted payment information contained in the magnetic stripe. In 2014, Obama administration brought the Buy Secure Initiative which aggressively pushed for the adoption of more secure chip technology in the U.S. credit market. The payment security technology in these cards is dramatically advanced and safer than the previous stripe cards. Every time a new transaction is done by a consumer using this chip technology, the microprocessor in the chip generates an unique transaction ID which is only known to the

always on the merchant.

lender and the chip. This transaction ID is generated for one transaction only and is not valid for the subsequent transactions. Hence, it became more difficult for the fraudsters to steal information from these cards. This effectively reduced the fraud risk faced by the lenders. In addition to Buy Secure initiative, around the same time there was introduction of EMV (Europay, MasterCard, Visa) liability shift by the lenders. This passed on the liability for fraudulent transactions processed without an EMV card reader on to the merchants. Specifically, in cases where the merchant, instead of using the chip reader, allows swiping of the card then the merchant is liable for the fraudulent charges.

Figure A.2 provides depiction of three example scenarios to understand the liability shift. In scenario 1, card present fraud with fake card; a skimmer can copy the information from the magnetic stripe using a skimming machine and can make a fake copy of the card. This was a very common practice before 2014. This fake card can then be used by the skimmer for a transaction at a merchant. Before 2014, the liability for this card present fraud with fake card was onto the lenders. However, after the roll out of chip cards, it became significantly difficult for the skimmers to make a copy of the chip card. A chip card's information can still be copied using the magnetic stripe at the back of the card however, the chip itself cannot be duplicated and the new fake card will only have a magnetic stripe not the chip. Due to EMV liability shift, if the merchant allows swiping of card instead of using the chip reader, then the merchant is liable for the cost of fraud not the lender. Scenario 2, card present fraud with a fake card; for example if a pick-pocketer gets hold of a real card and uses it for transactions at a merchant. Here, in both cases, before and after 2014, the lender is liable for the cost of fraud as the transaction happened using the real card and the merchant is following the best practices. In scenario 3, card not present fraud; if a fraudster gets hold of credit card information of a consumer without the actual card, this information can be used for e-commerce transactions. For this card not present fraud in both cases, before and after 2014, the merchant is liable for the fraudulent transaction not the lender. Overall, before 2014 for most of the fraudulent cases the lender was responsible for the cost of fraud.

Since the roll out of more secure cards and liability shift, the cost of most of the fraudulent transactions is passed to the merchants.

The enhanced payment security and the shift in liability onto merchants reduced the lenders' Value at Risk associated with the card present fraudulent transaction.

3 Data

3.1 Gies Consumer and small business Credit Panel

We use the Gies Consumer and small business Credit Panel[5] (GCCP) data set for our analysis. GCCP is a consumer credit reporting data[6] provided by a major U.S. credit bureau. This data set contains a random sample of about 1% of U.S. population of anonymized individuals who have credit reports with the credit bureau. The data set has annual snapshots of 2mn to 3mn individual credit reports taken in the first quarter of each year. The data set covers a period from 2004 to 2018.

A key advantage of the GCCP data is that it contains detailed annual information about each individual's reported credit line items such as mortgages, auto loans, credit cards etc. We restrict our sample to credit card for which we have information on credit limit, account balance, line open date, charge-off balance, delinquency, collection amount along with an unique anonymized lender id associated with individual's each credit card per annual snapshot. Further, the data set also contains individual demographic information on age, gender, marital status, state, zip code, and credit score. The credit score comes from the Vantagescore[7] model.

[5]See Fonseca (2023) for a detailed discussion on GCCP.
[6]See Gibbs et al. (2023) for a detailed discussion of the consumer credit report databases.
[7]Vantage credit score model has a credit score range between 300 and 850.

3.2 Sample Construction

For our sample construction, we only keep the credit lines where the account type is a credit card. To identify the credit cards with fraudulent transactions, we first select all the cards that are closed with a status flag of "Lost or Stolen". When a consumer raises a dispute against an unauthorized transaction on the credit card, the lender closes that card to prevent further misuse and issues a new replacement card with a new unique id to the consumer. The lender marks the old card as lost or stolen and updates the card's status as closed. In our data set, a lost or stolen credit card can continue to appear on the credit report for an un-defined number of years, even after being closed. Hence, to avoid duplication, we define a fraudulent card as the first instance of a credit card being reported closed as lost or stolen. Since, we have annual snapshots from the end of first quarter of each year, a credit card reported closed due to as lost or stolen during quarter 2 to quarter 4 of calendar year, will appear as a fraudulent credit card in our data set in the next annual snapshot. For example, if a credit card was reported stolen in July of 2006, it will be reported at the end of Q1 of 2007.

Figure 1 shows the distribution of the total number of credit cards reported as fraudulent per year. In total there are about 926,389 cards reported as fraudulent in our sample between 2005 to 2018[8]. It can be observed that there is a sharp decline in the number of fraudulent credit cards following the introduction of the more secure chip credit cards in the year 2014. From a peak of 114,913 in the year 2005, the number of such cards see a sharp decrease (of 78%) to about 25,791 in 2014. Since the roll out of more secure chip-enabled cards, the total reported number of fraudulent credit cards has kept steady around 26,000-28,000.

After identifying the fraudulent credit cards, we create a fraudulent event flag for each individual with such credit cards. A potential criticism is that we cannot observe *lost* and *stolen* cards separately. We broadly define a lost card as a card that is replaced without any

[8] The way our sample is constructed, we cannot separate new frauds from the previous frauds for the year 2004, hence, we don't use fraud flags from that year. We take credit outcomes data such as credit limit, account balance, utilization from 2004 required for the event study.

fraudulent transactions, and a stolen card is a card with fraudulent transactions. We do not believe that lenders would view these differently. A card that is lost, is simply one that has not yet been found by a criminal. While a consumer may have lost their card in their home, it could also be sitting in the back seat of a cab waiting for a fraudster to find and use it. One could argue that lenders are more receptive to lost cards as they did not observe the negative event of a fraudulent transaction. However, the lender should view these consumers as riskier since they have revealed themselves as careless with control of their cards. Even if lenders are indifferent to lost cards, this would bias against our results. If lost cards are no concern then this increases noise in our observation of fraud. Hence, any bias in our results due to these lost cards should go against our hypothesis that extending additional credit to the fraudulent card consumers, increases the cost for the lenders.

We are interested in seeing why the first fraud experience is associated with the lenders' decision of extending credit to consumers. For this Table 3 provides us with, conditional on having experienced first fraud, the likelihood of experiencing a fraud in next 1 year and next three years using an OLS analysis. Conditional on first fraud, a consumer is about 12% more likely to have fraud in next year and about 20% more likely to have fraud in next three years. Hence, having one fraud dramatically increases a consumer's likelihood of experiencing multiple frauds. Further, after the introduction of more secure cards, we see that the likelihood of having subsequent fraud decreases by half. Additionally, Figure A.3 shows the distribution of number of fraudulent events for consumers with at least one fraudulent event during the sample period. About 61% of the consumers experience credit card fraud only once, whereas about 24% consumers experience the fraud event at least twice in our sample.

In all our empirical analyses unit of observation is at a consumer-year level. To obtained this sample we sum the total credit limit, account balances etc., over all the active credit card lines for each consumer in an year. For heterogeneity analysis, we divide our sample into two sub-samples for low credit and high credit score. A consumer is in low credit sample if their credit score was less than 600, whereas a high score consumer has credit score of more than 719 three years prior to the fraudulent event.

3.3 Summary Statistics

Table 1 reports the summary statistics for the full sample from GCCP. An average individual has total credit limit of $31,690, total credit card balance of $4,660, a credit score of 699, holds about 4 cards and has a likelihood of 3.2% for reporting a fraudulent event during the sample period. Whereas, the median consumer has total credit limit of $15,000, total credit card balance of $870, a credit score of 710, holds about 3 cards during the sample period.

Column 1-3 of Table 2 report the summary statistics for consumers before the introduction of chip-enabled credit cards through BuySecure initiative in 2014. Column 4-6 of Table 2 report the summary statistics for consumers after BuySecure initiative in 2014. We see that the likelihood of a consumer experiencing a fraudulent event before 2014 was 4.22%. Post the technology shock of 2014 the likelihood of fraudulent experience decreases to 1.2%.

3.4 D-i-D Matching Sample

We define a treated consumer as one who has experienced a fraudulent event during the sample period, and a control consumer is defined as one who never experiences a fraudulent event. Table A.1 reports the summary statistics for treated and control consumer in the full sample period of 2004 to 2018. It is evident that the treated and control consumers are different in many dimensions, therefore we employ nearest neighbor matching to find reasonable controls for the treated consumers.

In line with the recent literature on the stacked difference-in-differences (Goodman-Bacon (2021), Callaway and Sant'Anna (2021), Sun and Abraham (2021)) to construct a matched control group, we match our treated individuals with consumers (controls) who have never experienced a fraudulent event during the sample period. Treated consumers are matched with controls three years before the treated consumers' first fraudulent event within the same state and year. We further put a restriction on our matched sample that the controls should have information for continuous three years in the pre-event period. Then we do nearest neighbor match on income, credit limit, account balance and credit score. Our choice of matching characteristics is guided by the fact that these are the same characteristics that lenders observe and plausibly account for, while deciding on extension of credit to the consumers. The matched groups consists of five controls[9] for one treated and the matching is done with replacement, that means that a control can be a match for more then one treated consumer. The controls provide a counterfactual of the evolution of credit outcomes for individuals, who are similar on observable characteristics, in case of absence of a fraudulent event.

Figure 2 plots the estimates from balancing regressions for standardized covariates used for matching sample. Each balancing regression compares treated consumers to control consumers. Table A.2 provides the descriptive statistics of the matched treated and control consumers along with the p-value from t-test conducted to assess the quality of matching, at the time of matching i.e. three years before the fraudulent event, respectively. The average credit limit for treated is \$40,246 and for control it is \$40,216. The treated sample's account balance is just \$80 more than the control's account balance of \$5,489. Both the groups have same average credit score of 722. The balance plots along with the t-test suggests that our matching procedure finds controls who are similar to treated consumers in observed matching characteristics at the time of matching.

Overall, our matching procedure results in groups of treated and control consumers who are similar in their observed characteristics of credit limit, balance, and credit score.

A consumer can experience multiple fraudulent events in their lifetime (see Figure A.3) however, we face certain econometric challenges in analyzing these multiple treatments. In addition of having a staggered introduction of treatments, the treated units in the sample

[9] A concern with high number of matching could be that the quality of matching gets affected. However, due to GCCP's well populated and large data set, we do not see deterioration in our matching quality compared to when we have three control.

can have multiple treatments. Since, our empirical strategy is going to use a difference-in-differences matching estimator technique, we would ideally want to match consumers with more than one treatments with consumers who are treated only once. Further, we would need to match on the treatment year which would potentially reduce the estimation power. Also, we need to disentangle the effect of subsequent frauds, for this we will need to set a minimum distance between future treatments. Therefore, we focus our study only on the first instance of a fraudulent event experienced by the consumer.

4 Difference-in-differences Event Study

4.1 Empirical Strategy

We investigate the time series dynamics of credit outcomes for treated individuals around the fraudulent event using a difference-in-differences event study design. We present our results by creating an event window of three years before and three years after the fraudulent event.

Our main specification estimate the following at consumer-year level:

$$Y_{i,t} = a + \sum_{j=-3}^{3} \alpha_j \ (LS_i \times D_{t-j}) + \sum_{j=-3}^{3} \beta_j \ (LS_i \times D_{t-j} \times Post_{2014}) + \delta_{g,t} + \eta_{i,g} + \varepsilon_{i,t} \qquad (1)$$

where $Y_{i,t}$ is the credit outcome of interest (credit limit, number of credit card inquiries, number of new credit cards, etc.) for consumer i at time t. LS_i is a dummy which takes a value of one if a person ever experience a fraudulent event, 0 otherwise. D_{t-j} is the event time dummy for three years before and three years after the event. $Post_{2014}$ is a dummy which takes value 1 for observations in or after the year 2014, 0 otherwise.

Our coefficient of interest is β_j, which measures the average change in credit outcomes for consumers with a fraudulent event post the technology shock relative to a consumer with a fraudulent event prior to the technology shock of 2014. $\delta_{g,t}$ are matched group by calendar year fixed effects that control for time-varying unobserved heterogeneity across groups.

Effectively with this matched group-by-year fixed effect the unobserved correlated shocks to the matching characteristics of the groups with the fraudulent event are being absorbed. $\eta_{i,g}$ are the individual by group fixed effect to remove the time-invariant heterogeneity among individuals across groups. Since we draw controls with replacement, individual fixed effects are insufficient. We want to remove the average of each person within each group. We double cluster the standard errors at individual by group fixed effect and year level. [10]

4.2 Access to Credit

Figure 3, Panel (a) plots the triple difference-in-differences estimation coefficient β_j. We find that after the improvement in payment security, average treated consumer sees an economically meaningful increase of credit by about \$3,071, (7.6% relative to the average of \$40,246). This result indicate that the improved payment security has a positive effect on credit availability for fraud exposed households.

Figure 3 Panel (b) plots the credit limit associated with average fraud experience before (α_j) and after ($\alpha_j + \beta_j$) the technology shock. α_j; estimates the change in credit limit for a treated consumer relative to the matched controls in before the technology shock of 2014. Two important facts of the treatment effect are evident. First, in the pre- event period there is an increasing trend in the total credit limit for the treated consumers relative to the control consumers. Second, experiencing a fraudulent event is associated with the leveling off in treated consumer's credit limit relative to the control group even after three years of the fraudulent event. This result is consistent with lenders' willingness to extend high spending consumers more credit to maximize their revenue prior to the credit card fraud. Since the cost of fraudulent transactions is to be borne by the lender, these high spending consumers become more risky after the fraudulent event. Therefore, the lenders are less willing to extend additional credit to these consumers.

We believe that the increasing pre-trend of credit limit might be because these consumers

[10] Our results are robust to the choice of person or year clustering. Our main specification clusters at individual by group fixed effect and year which is the unit of randomization for the treatment of fraud.

spend more than their matched controls, which means they generate more revenue. The lenders are willing to extend them more credit relative to their peers. Ideally, to account for the pre-trend we would want to match on spending behavior, however we don't have spend information in the GCCP data. Therefore, we use credit card account balance as a crude proxy for spending behavior and run our main specification 1. From Figure A.5, it can be observed that in the pre-event period the treated consumers indeed have more balances relative to their control peers.

$\alpha_j + \beta_j$ in Figure 3, Panel (b); estimate the change in credit limit for a consumer who was treated after the technology shock relative to the matched control group. Two important facts of the treatment effects are evident. First, as before, we observe an increasing trend in the total credit limit of the treated consumers in the period before the fraudulent event. Second, experiencing a fraudulent event with enhanced payment security is associated with a continued increasing trend in the total credit limit for treated consumers. This can be reconciled with the dramatic decrease in fraud probability after 2014 and a shift of liability from the lenders to merchants. Hence, post technological innovation in payment security we find that treated consumers become less risky for lenders. Now, more credit is available to these fraud exposed consumers.

4.2.1 Cohort Analysis

We examine whether experiencing a fraudulent event prior to the technology shock is associated with a change in the credit outcomes for the consumers starting year 2014. We employ a difference-in-differences event study by calendar-year.

The specification is

$$Y_{i,t} = b + \sum_{j=-3}^{3} \gamma_j \ (LS_i \times D_{t-j}) + \delta_{g,t} + \eta_{i,g} + \varepsilon_{i,t} \tag{2}$$

where $Y_{i,t}$ is the credit limit for consumer i at time t. LS_i is a dummy which takes a value of one if a person ever experience a fraudulent event, 0 otherwise. D_{t-j} is the event time dummy for three years before and three years after the event.

Here, the coefficient of interest is the difference-in-differences coefficient; γ_j which measures the average change in credit limit for a consumer with a fraudulent event relative to a consumer without any fraudulent event. $\delta_{g,t}$ are matched group by calendar year fixed effects that control for time-varying unobserved heterogeneity across groups. $\eta_{i,g}$ are the individual by group fixed effect to remove the time-invariant heterogeneity among individuals across groups. We double cluster the standard errors at individual by group fixed effect and year level.

Figure 4 provides the event-study coefficients of the difference-in-differences estimation i.e. γ_j for different cohorts (2011-2014). This coefficient estimates the change in credit limit for a treated consumer relative to the matched control group. The first figure shows the results for cohort treated in 2011, we find that the credit limit for the treated consumers increases before the fraudulent event and after the event, the increasing trend of the credit limit levels off. However, at t+3 (i.e. 2014) we find that these cohorts get a sudden jump in their total credit limit. Similarly, for 2012 and 2013 event-year cohort we see that the credit limit first decreases and then there is a significant increase in the year 2014. For event-year cohort 2014 (and onward) we see that an increasing trend in the credit limit continues. Our results indicate that the even the prior treated cohorts get an improved access to credit after the introduction of BuySecure initiative.

4.3 Household Response

We want to examine how improved payment security affects consumers behavior upon exposure to fraud. We run our main specification 1 separately for two sub-samples; high credit score consumers and low credit score consumers. The sub-sample analysis informs us if there is a heterogeneous response by households.

Our outcomes of interest are number of new credit cards opened in past six months, total number of credit cards, number of card inquiries in past six months and balance amount on credit cards. We construct a dummy variable; card closure, which takes value 1 when a card is closed due to reasons other than fraud. These variables help us disentangle if the increased credit limit is from supply side or from demand side. If the effect on credit limit is from consumer demand instead of credit supply, then we should see an accompanied increase in number of new credit cards opened, number of card inquiries, balance amount on credit cards etc. However, if the consumers develop a distrust in financial system then we should see a decrease in credit demand post exposure to fraud. We also create a dummy for likelihood of 90+ days past due on credit cards as a measure of financial distress faced by households.

Figure 5 and 6, plot the triple difference-in-differences estimation coefficient β_j from our main specification 1 for low credit score and high credit score samples, respectively. This coefficient measures the average outcome for a consumer who experienced fraudulent event after technology shock relative to the consumer who experienced fraud before the technology shock. We find that there is no significant change in consumer response due to the technology shock.

We then look at consumer response associated with credit card fraud. We find that low credit score consumers are more likely to reduce demand for credit, see Figure 7, 8, and 9. This trend is similar in both periods; with and without the technological innovation in payment security. Our finding are consistent with consumers developing a distrust in the payment security and thus, reducing their credit demand. Additionally, low credit score consumers are more likely to face financial distress, see Figure 10. We also look at bankruptcy flag in last seven years (see Figure A.7) and find no effect around the fraudulent event. This might be because the average default amount of a few hundred dollars is not significant enough to induce bankruptcy.

Since, low credit score is associated with low income and less financial sophistication, these results suggests that poor households are experiencing a greater shock to trust in payment security compared to high credit score consumers.

5 Conclusion

In conclusion, our study provides critical insights into the effects of financial fraud and technological innovations in payment security on consumer credit outcomes. We find that while the introduction of chip-enabled credit cards under the BuySecure initiative significantly reduced fraud and increased credit access for consumers, it did not restore consumer confidence, especially among those with low credit scores. We further find that low credit score consumers are more likely to face financial distress when exposed to fraud. This persistent lack of trust highlights the need for further policy innovations, such as one-time passcode for credit card transactions and sufficient financial education to consumers.

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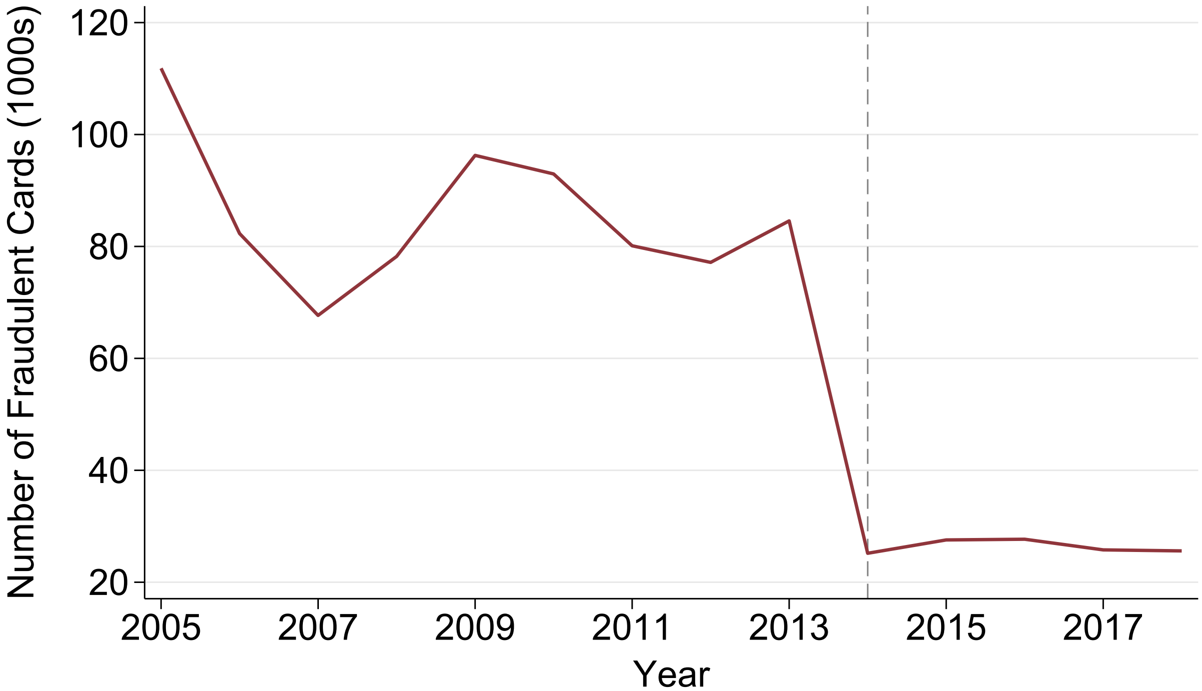
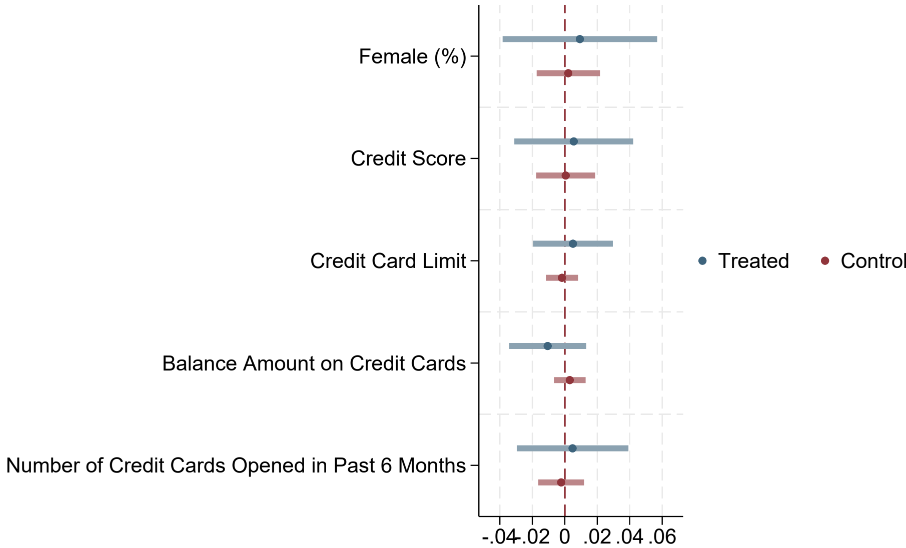
Figure 1: Fraudulent Credit Cards



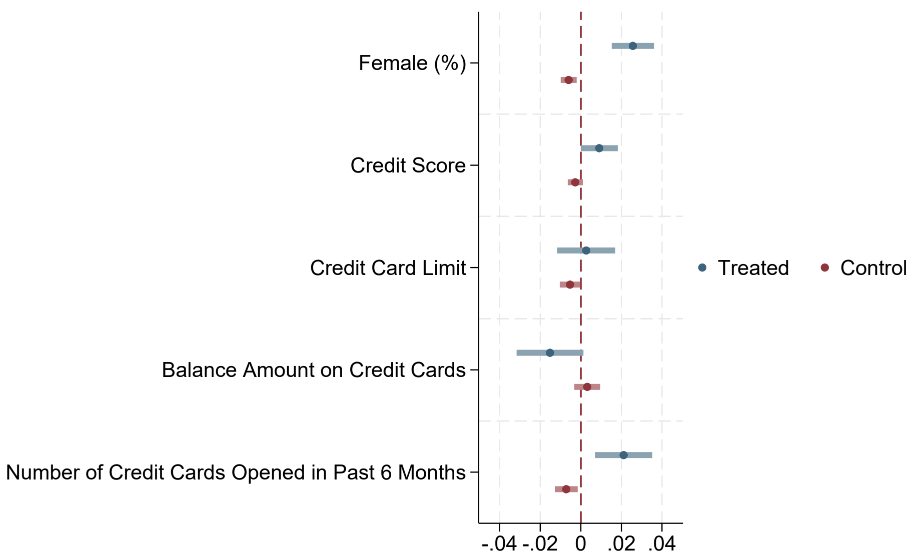
Notes: This figure shows the number of credit cards which experienced fraud by year, from 2005 to 2018. The gray dashed line represents BuySecure initiative of 2014 which pushed for widespread adoption of more secure chip enabled credit cards in the U.S. credit card market.

Figure 2: Matched Sample Covariate Balance Plot

(a) Low Credit Score Consumers



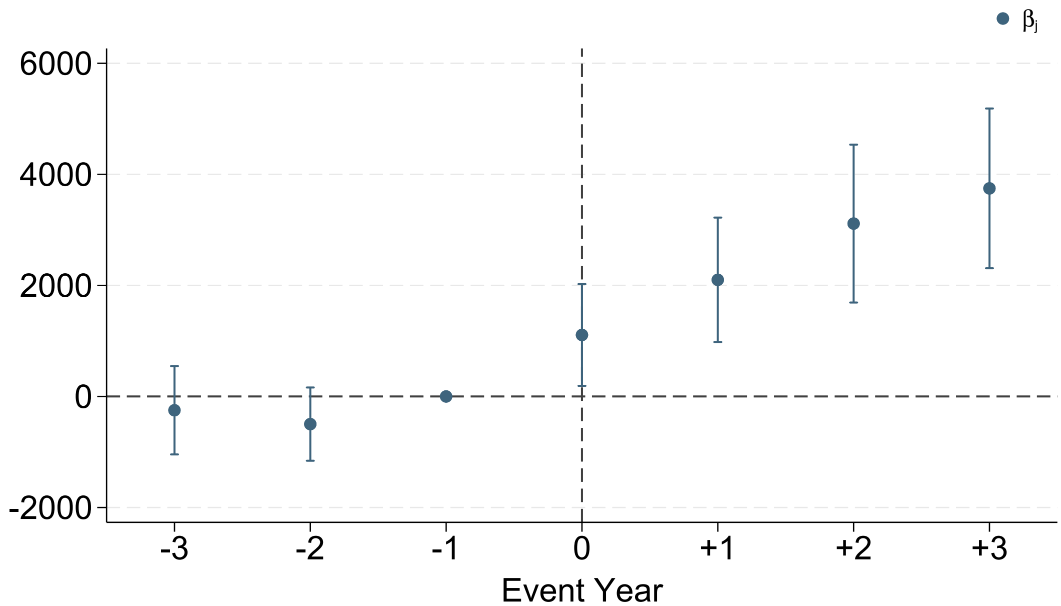
(b) High Credit Score Consumers



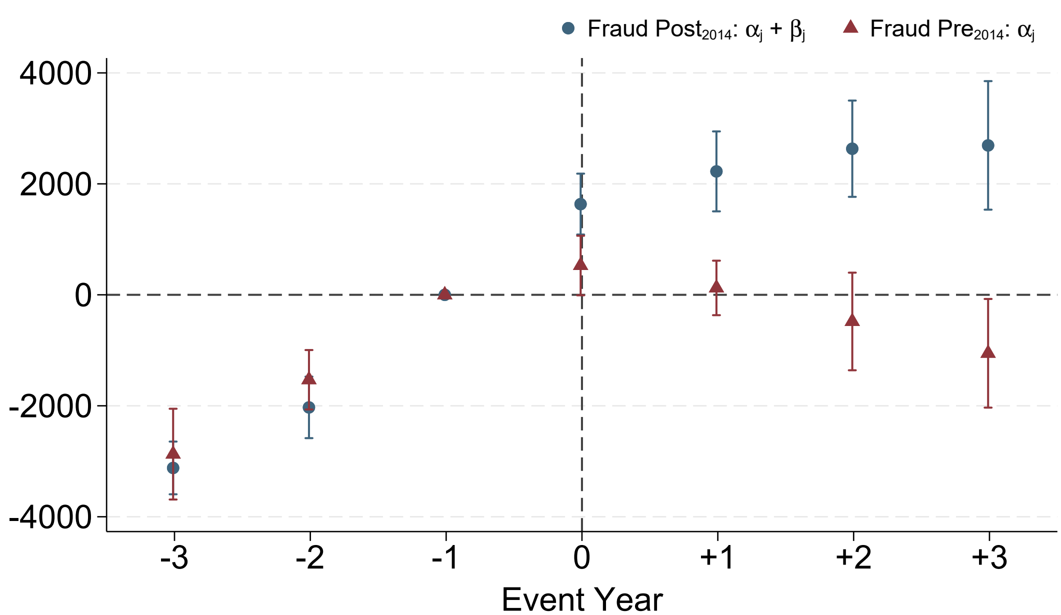
Notes: This figure shows estimates from balancing regressions for selected outcomes. Each balancing regression compares treated consumers to control consumers. All variables are standardized, and each dot represents the regression coefficient of the variable labeled on the y-axis, regressed on either the treated (blue) or control (red) consumer indicator. Panel (a) shows balance plot for low credit score sub-sample. Panel (b) shows balance plot for high credit score sub-sample.

Figure 3: Access to Credit: Credit Card Limit ($)

(a) Triple Difference

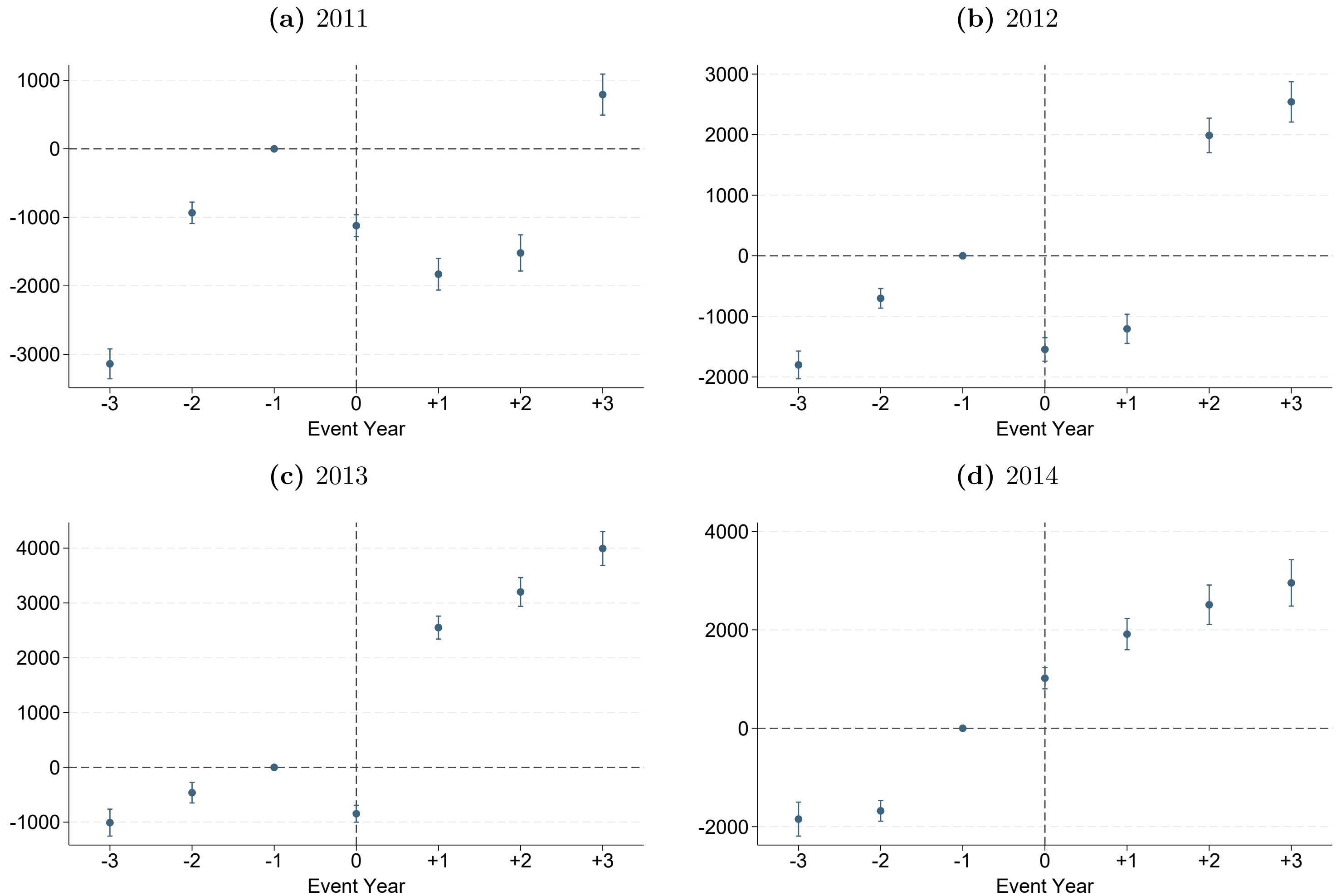


(b) Pre- and Post- Technology Shock



Notes: Panel (a) shows the event study coefficients of the triple difference-in-differences estimation i.e. β_j and 95% confidence interval from our main specification 1. Panel (b) shows the event study coefficients of the difference-in-differences estimation i.e. α_j, $\alpha_j + \beta_j$ and 95% confidence interval from specification 1. The outcome variable is the total credit limit across a consumer's all credit cards.

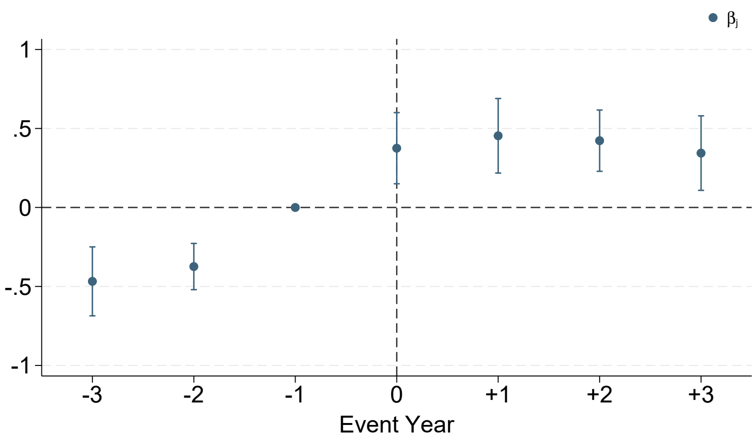
Figure 4: Access to Credit: Credit Card Limit ($), Cohort Analysis



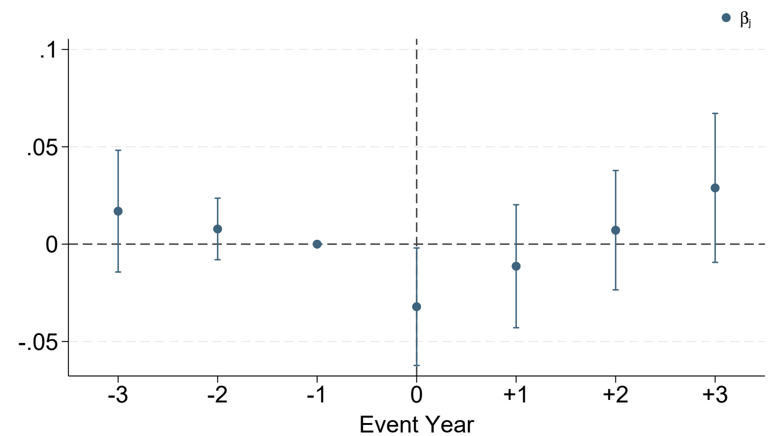
Notes: This figure shows coefficient estimates and 95% confidence intervals of Equation 2 by cohorts from 2011 to 2014. Credit Card Limit is the total credit limit across a consumer's all credit cards.

Figure 5: Household Response: Credit Demand and Financial Distress, Low Credit Score Consumers

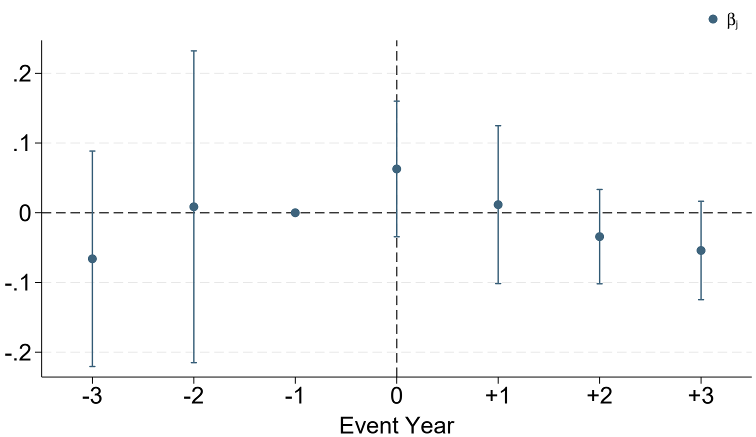
(a) Number of Credit Cards Opened in Past 6 Months



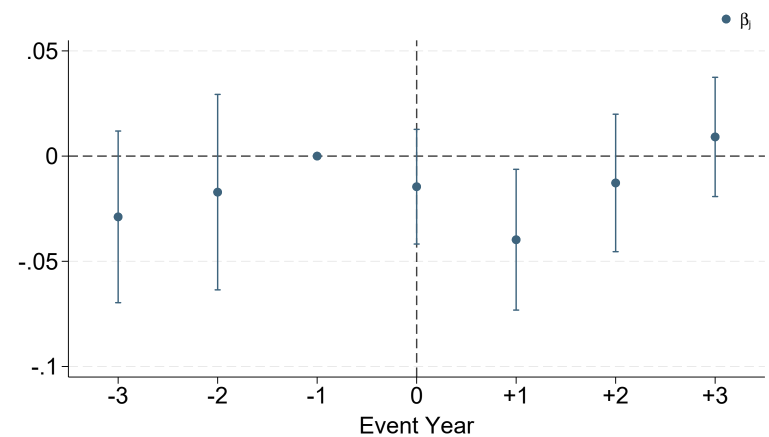
(b) Likelihood of Credit Cards Closure (%)



(c) Number of Credit Card Inquiries in Past 6 Months



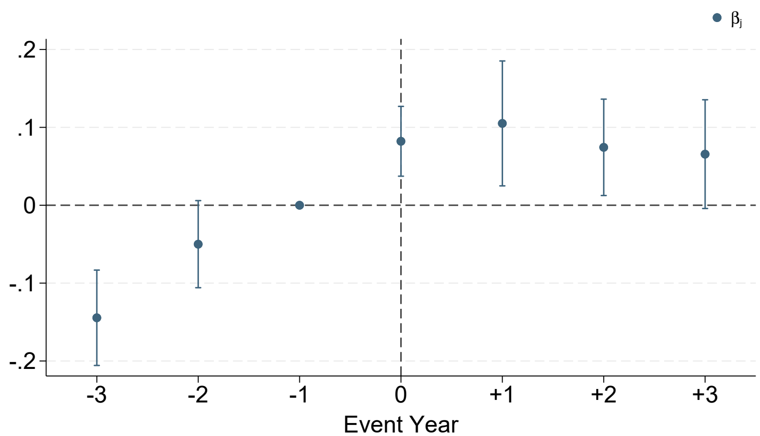
(d) Likelihood of 90+ Days Past Due Credit Cards (%)



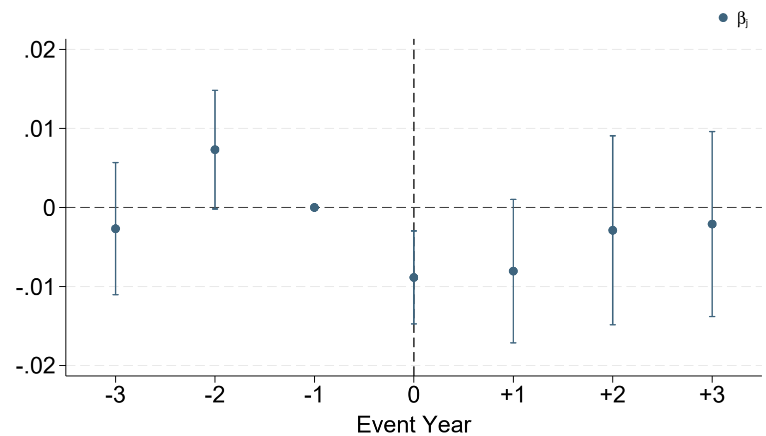
Notes: This figure shows the event study coefficients of the triple difference-in-differences estimation i.e. β_j and 95% confidence interval from our main specification 1 for the low credit score consumers sample.

Figure 6: Household Response: Credit Demand and Financial Distress, High Credit Score Consumers

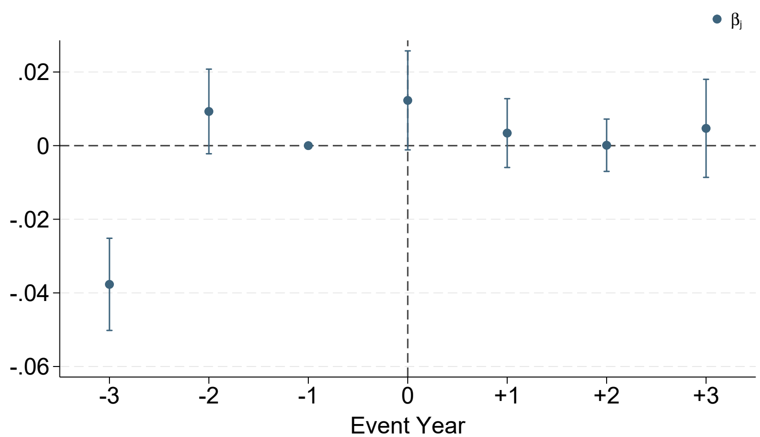
(a) Number of Credit Cards Opened in Past 6 Months



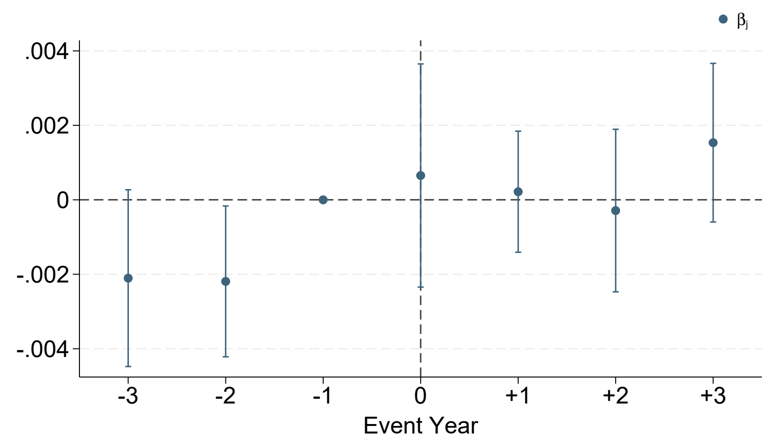
(b) Likelihood of Credit Cards Closure (%)



(c) Number of Credit Card Inquiries in Past 6 Months



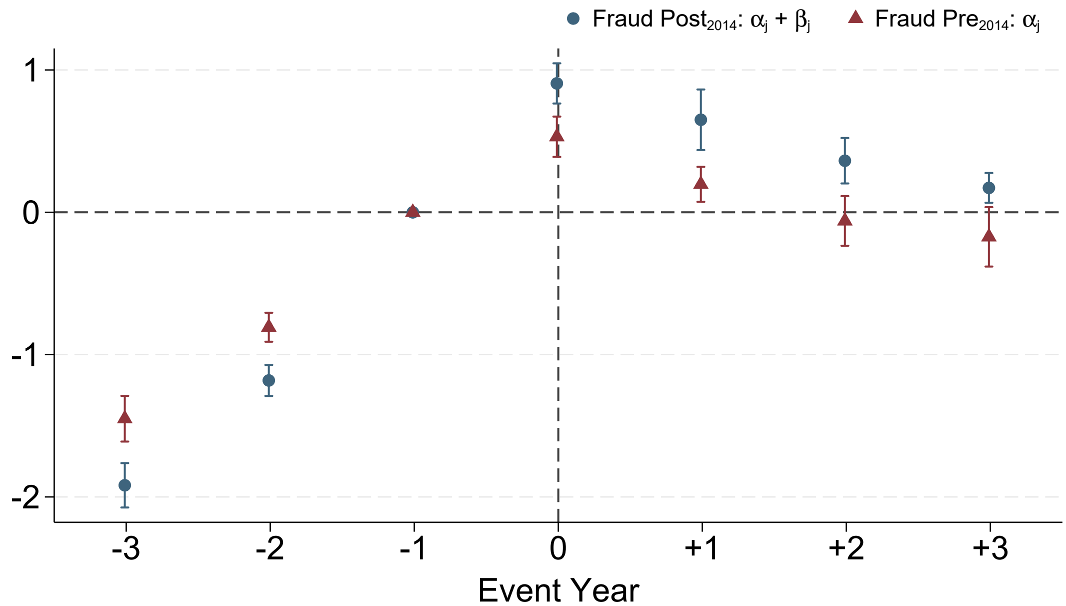
(d) Likelihood of 90+ Days Past Due Credit Cards (%)



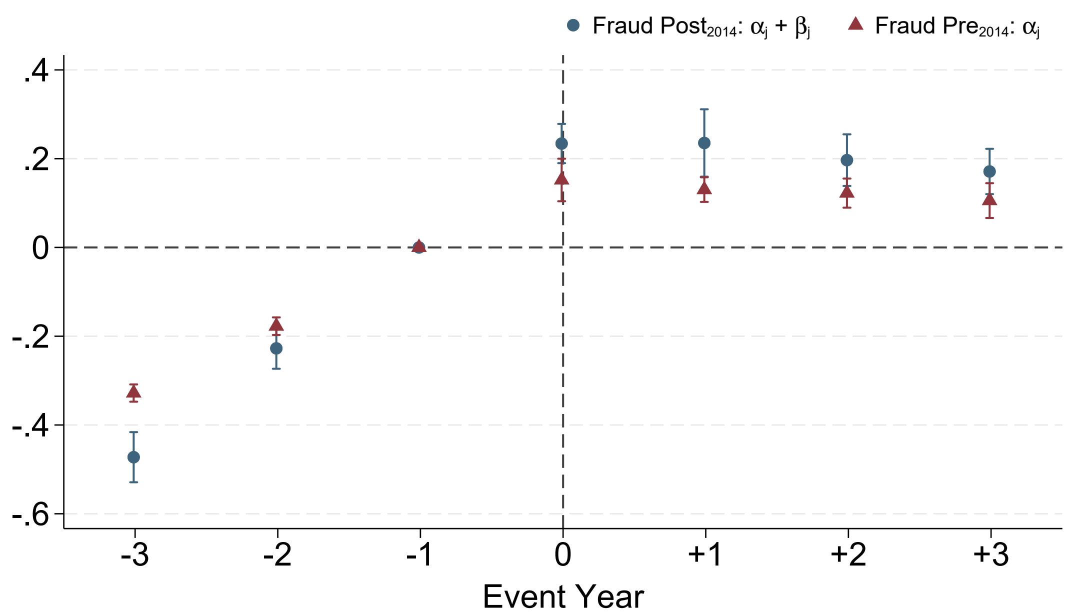
Notes: This figure shows the event study coefficients of the triple difference-in-differences estimation i.e. β_j and 95% confidence interval from our main specification 1 for the high credit score consumers sample.

Figure 7: Household Response: Number of Credit Cards Opened in Past 6 Months

(a) Low Credit Score Consumers



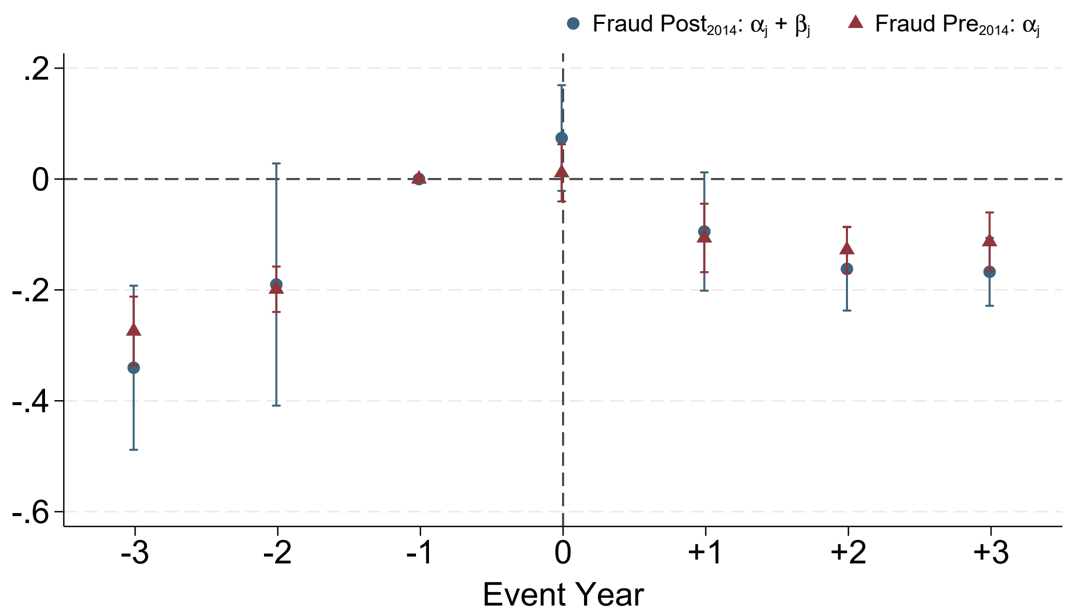
(b) High Credit Score Consumers



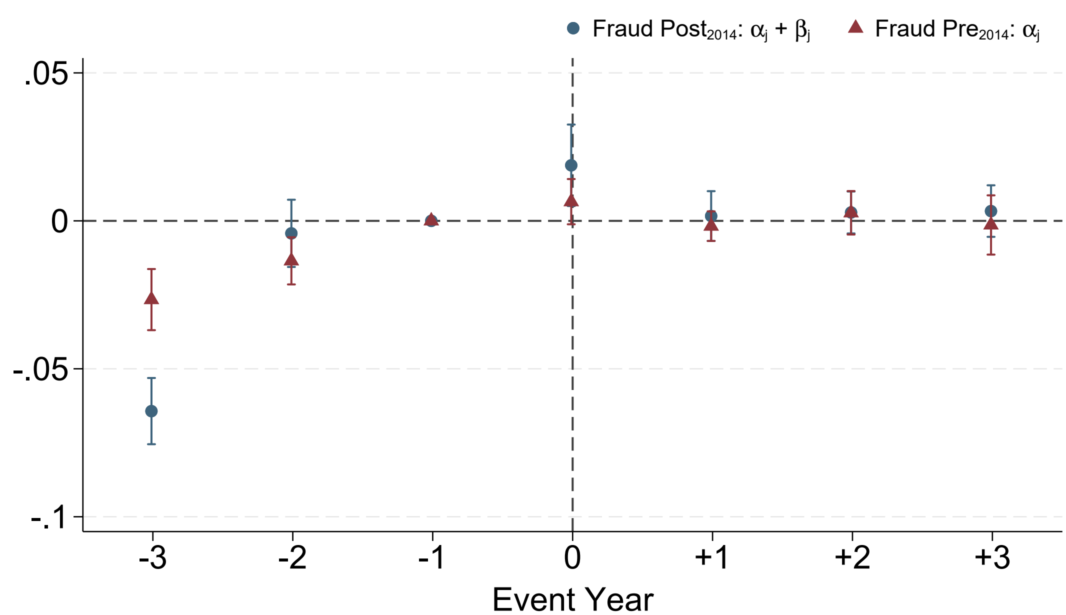
Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is the number of credit cards opened in past 6 months.

Figure 8: Household Response: Credit Card Inquiries

(a) Low Credit Score Consumers



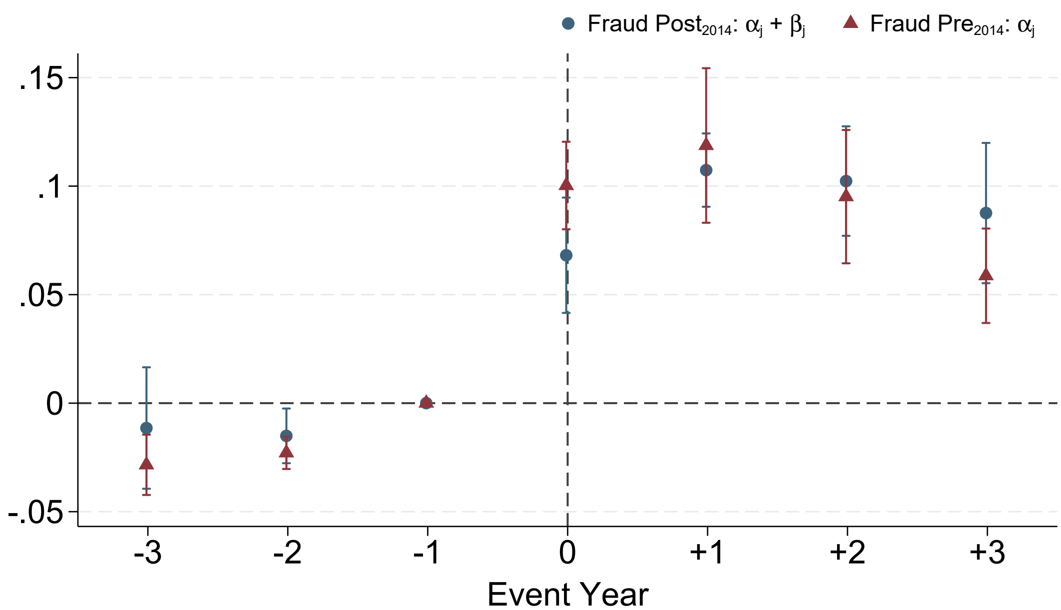
(b) High Credit Score Consumers



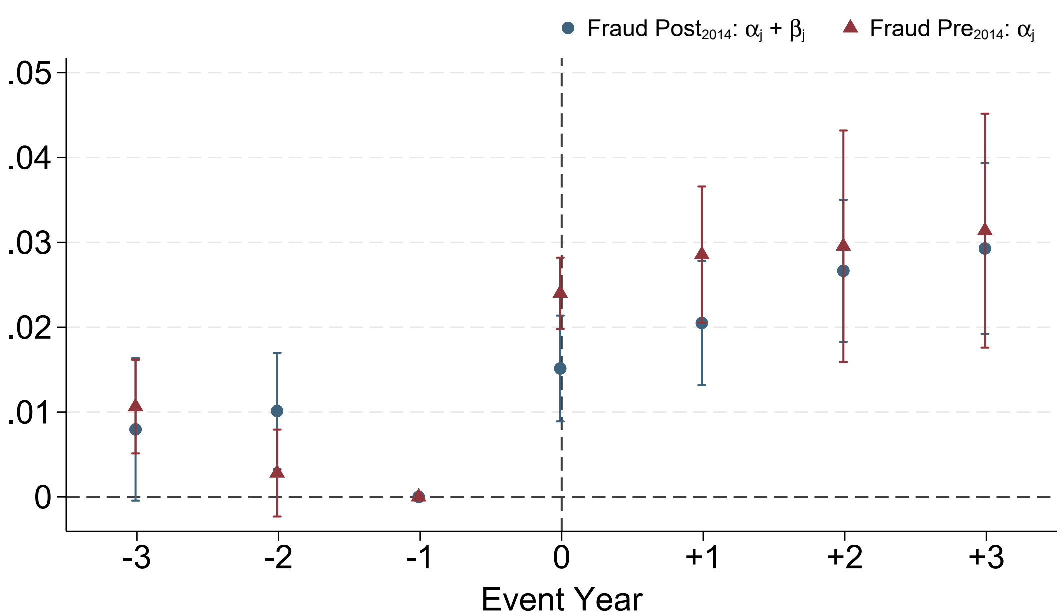
Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is the number of credit card inquiries in past 6 months.

Figure 9: Household Response: Likelihood of Credit Cards Closure (%)

(a) Low Credit Score Consumers



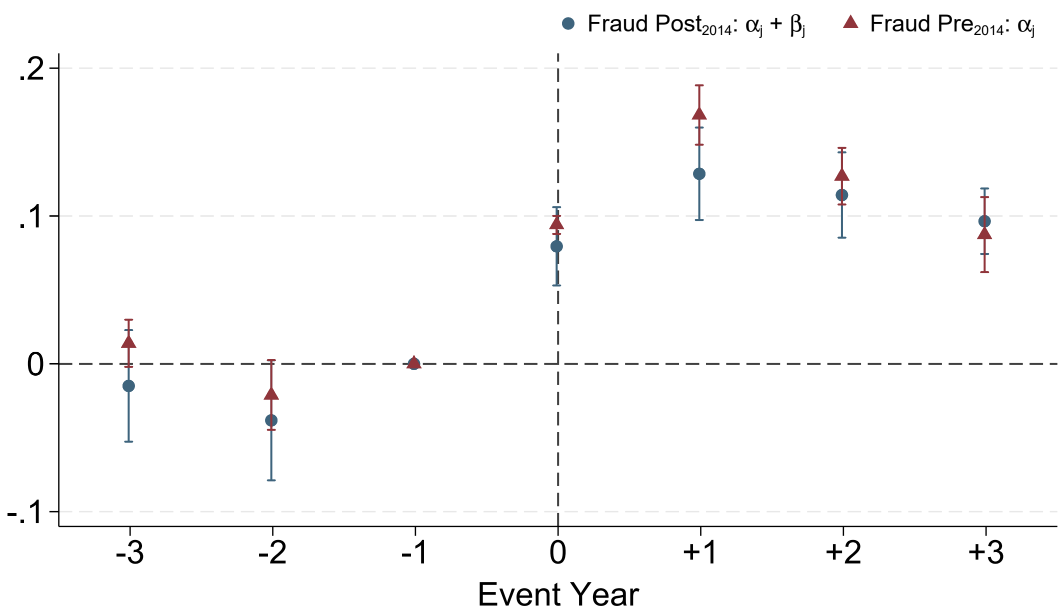
(b) High Credit Score Consumers



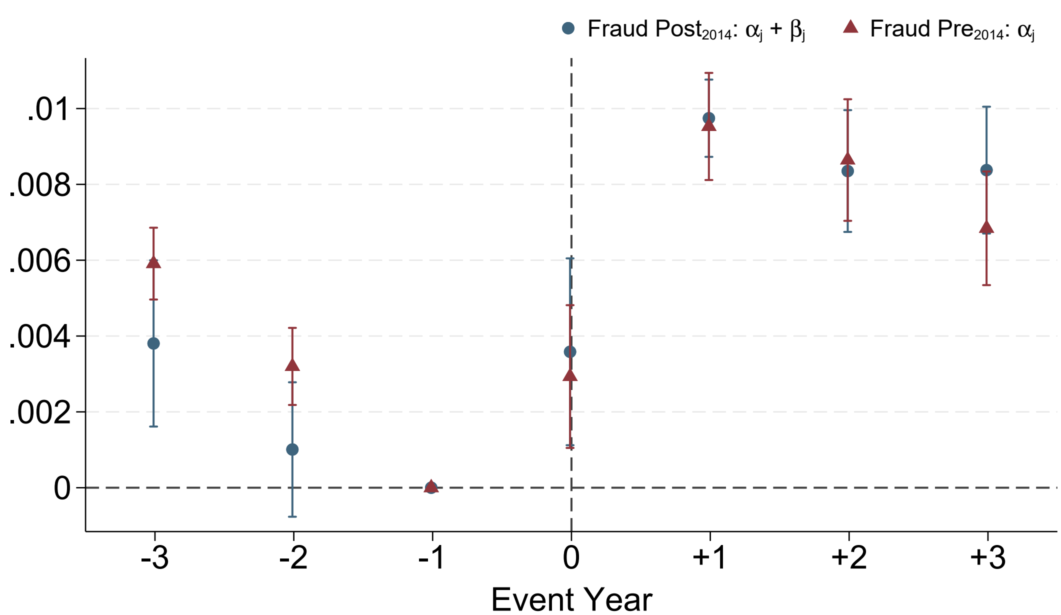
Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is the likelihood of closing credit card(s) due to reasons other than fraudulent events.

Figure 10: Household Response: Likelihood of 90+ Days Past Due Credit Cards (%)

(a) Low Credit Score Consumers



(b) High Credit Score Consumers



Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is the likelihood of being 90+ days past due on credit card(s).

Table 1: Summary Statistics for Full Sample

	(1)	(2)	(3)
	Mean	St. Dev.	Median
A. Demographics			
Female (%)	52.06	49.96	100.00
Age (years)	47.61	16.96	47.00
Income ($1,000)	48.00	26.07	41.00
B. Access to Credit			
Credit Score	698.69	97.56	710.00
Credit Limit ($1,000)	31.69	42.47	15.01
Balance Amount on Credit Cards ($1,000)	4.66	10.06	0.87
Balance Amount on Credit Cards 90+ Days Past Due	0.01	0.24	0.00
Credit Card Utilization (%)	20.32	31.22	4.00
Number of Credit Cards	4.35	4.44	3.00
Number of Credit Cards Opened in Past 6 Months	3.54	3.78	2.00
Number of Cards Inquiries in Past 6 Months	0.47	0.82	0.00
C. Financial Distress			
Credit Card Closure (%)	7.72	26.69	0.00
Number of Credit Cards 90+ Days Past Due	0.08	0.57	0.00
Credit Cards 90+ Days Past Due (%)	3.84	19.22	0.00
D. Fraud Experience			
Credit Card Fraud (%)	3.18	17.53	0.00
Observations	29,095,197		

Notes: This table presents summary statistics from the Gies Consumer and Small Business Credit Panel. The statistics are based on data from 2004-2018. The unit of observation is the consumer. The sample is limited to consumers with a non-missing credit score who had at least one credi card account in the smaple period.

Table 2: Summary Statistics for Before and After the BuySecure Initiative of 2014

	(1)	(2)	(3)	(4)	(5)	(6)
	Before			After		
	Mean	St. Dev.	Median	Mean	St. Dev.	Median
A. Demographics						
Female (%)	52.16	49.95	100.00	51.89	49.96	100.00
Age (years)	45.98	16.38	45.00	50.57	17.58	50.00
Income ($1,000)	46.61	24.71	40.00	50.64	28.31	42.00
B. Access to Credit						
Credit Score	694.13	96.86	706.00	707.38	98.30	720.00
Credit Limit ($1,000)	32.18	43.19	15.13	30.76	41.04	14.90
Balance Amount on Credit Cards ($1,000)	4.81	10.50	0.84	4.37	9.15	0.92
Balance Amount on Credit Cards 90+ Days Past Due	0.02	0.25	0.00	0.01	0.20	0.00
Credit Card Utilization (%)	19.91	31.67	3.00	21.11	30.33	5.00
Number of Credit Cards	4.47	4.54	3.00	4.13	4.25	3.00
Number of Credit Cards Opened in Past 6 Months	3.61	3.84	3.00	3.42	3.68	2.00
Number of Cards Inquiries in Past 6 Months	0.49	0.86	0.00	0.42	0.75	0.00
C. Financial Distress						
Credit Card Closure (%)	9.37	29.14	0.00	4.58	20.90	0.00
Number of Credit Cards 90+ Days Past Due	0.09	0.60	0.00	0.07	0.52	0.00
Credit Cards 90+ Days Past Due (%)	4.07	19.76	0.00	3.40	18.12	0.00
D. Fraud Experience						
Credit Card Fraud (%)	4.22	20.10	0.00	1.19	10.85	0.00
Observations	19,074,151			10,021,046		

Notes: This table presents summary statistics from the Gies Consumer and Small Business Credit Panel. The statistics are based on data from 2004-2018. The unit of observation is the consumer. The sample is limited to consumers with a non-missing credit score who had at least one credi card account in the smaple period.

Table 3: Propensity of Fraud

Dependent Variable:	Fraud in 1 Year		Fraud in 3 Years	
	(1)	(2)	(3)	(4)
L.First Fraud	0.12***	0.12***	0.20***	0.19***
	-0.00	(0.00)	(0.00)	(0.00)
Post_{2014}	-0.02***		-0.06***	
	(0.00)		(0.00)	
L.First Fraud × Post_{2014}	-0.0584***	-0.06***	-0.09***	-0.09***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.02***	0.01***	0.05***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Year FE	No	Yes	No	Yes
Control	Yes	Yes	Yes	Yes
Observations	27,253,374	27,253,374	27,253,374	27,253,374
R-squared	0.026	0.026	0.048	0.050

Notes: The table shows the results of ordinary least square regression for likelihood of future fraud conditional on experiencing a fraud. The unit of observation in each regression is a consumer-year. The outcome variable in columns 1–2 is the dummy for fraudulent experience in next year and in column 3-4 is the dummy for fraudulent experience in next three years. First Fraud is a dummy which takes value 1 for the first instance of fraudulent experience faced by the borrower. Post_{2014} is a dummy which takes value 1 if the observation year is 2014 or later. The bottom rows specify the fixed effects and control which is the number of cards. Standard errors (in parentheses) are clustered at the borrower level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

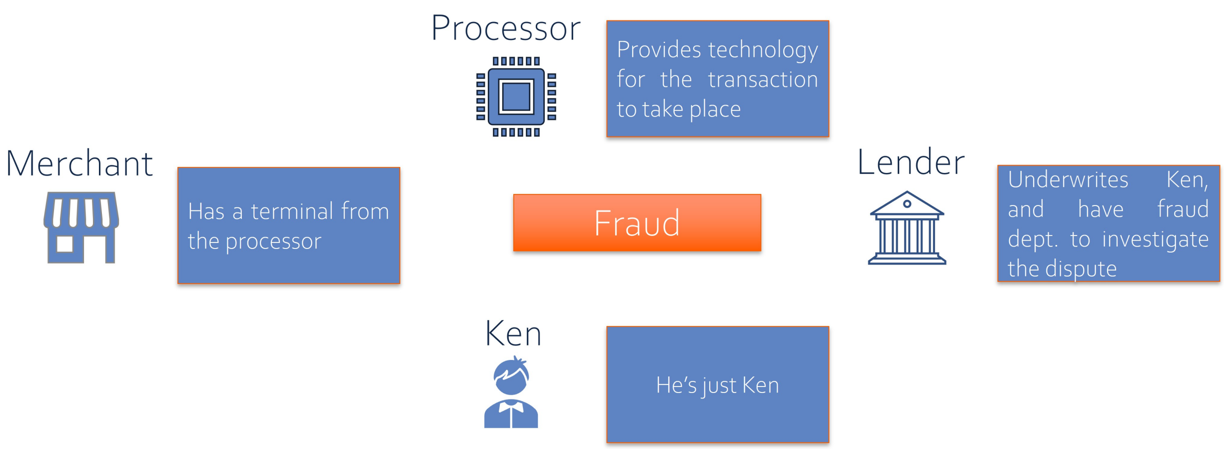
Online Appendix

House of Stolen Cards: Does Payment Security Improve Credit Outcomes for Households?

Divij Kohli & Justin Mohr

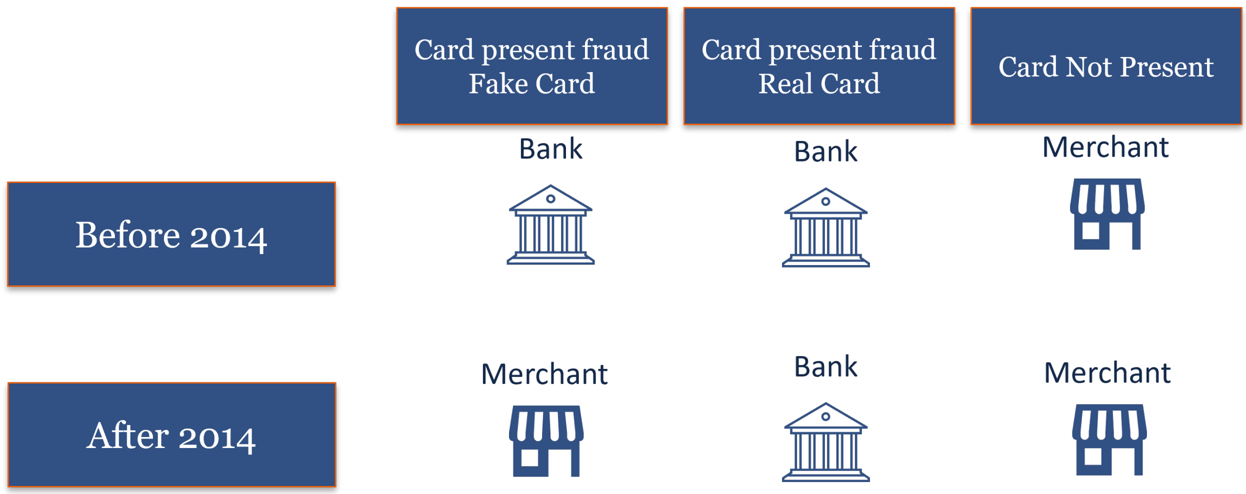
A Additional Figures and Tables

Figure A.1: Credit Card Transaction



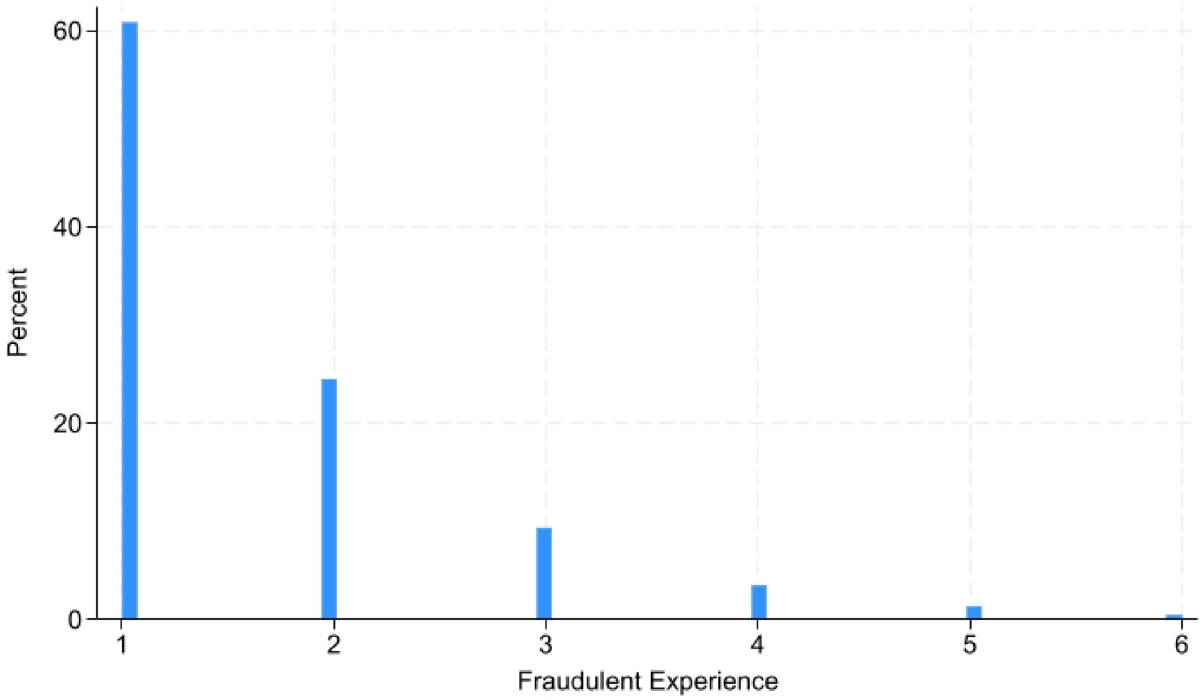
Notes: This figure shows four parties involved in a transaction using credit card; the consumer Ken, Ken's lender, the processor and the merchant.

Figure A.2: Fraudulent Transactions Liability



Notes: This figure shows the three scenarios for different type of credit card frauds and who bears the cost of the fraud. In 2014 chip cards were introduced to the U.S. credit card market. This was followed by fraud liability shift from lenders to merchants for most cases.

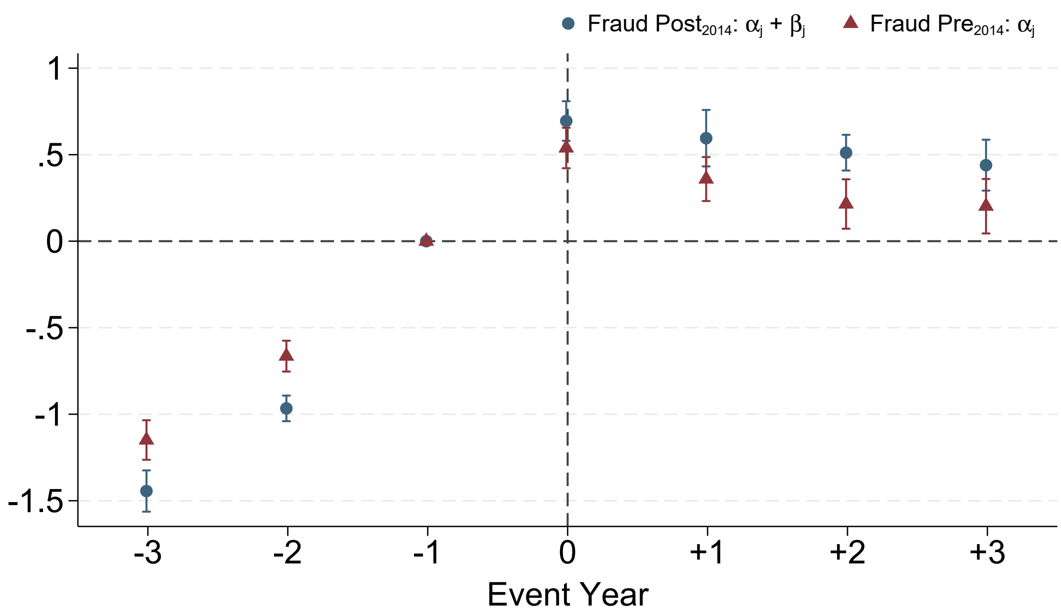
Figure A.3: Distribution of Fraudulent Experience



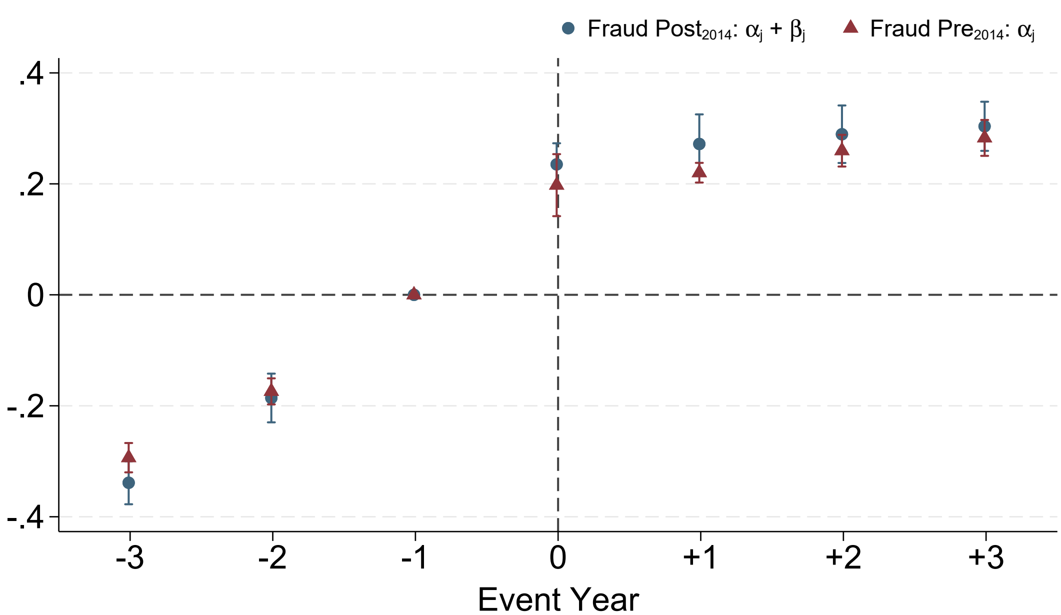
Notes: This figure shows the distribution of the number of fraudulent events for consumers with at least one fraudulent event in our sample.

Figure A.4: Household Response: Number of Credit Cards

(a) Low Credit Score Consumers



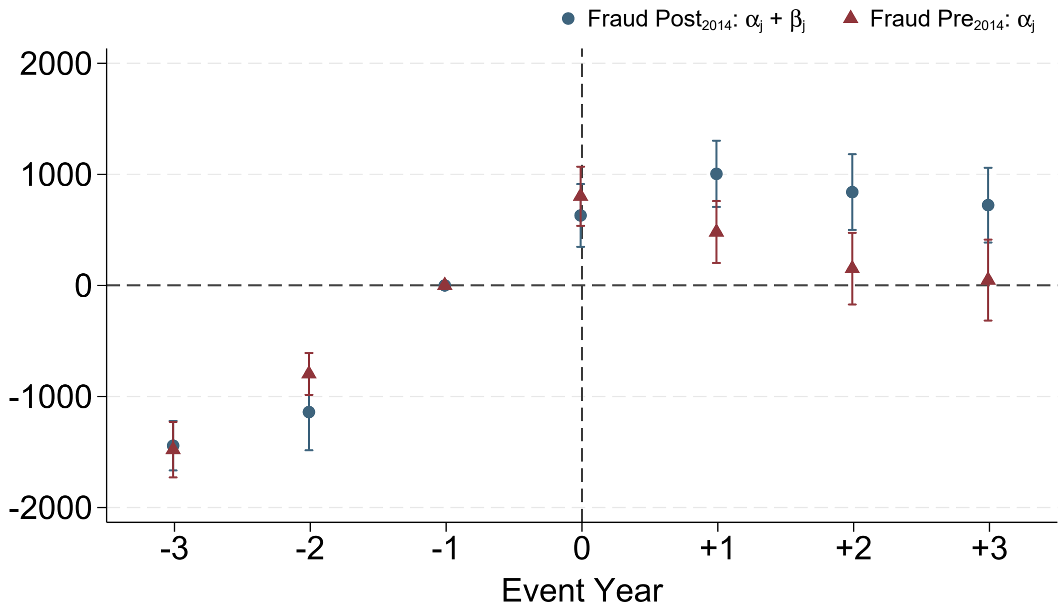
(b) High Credit Score Consumers



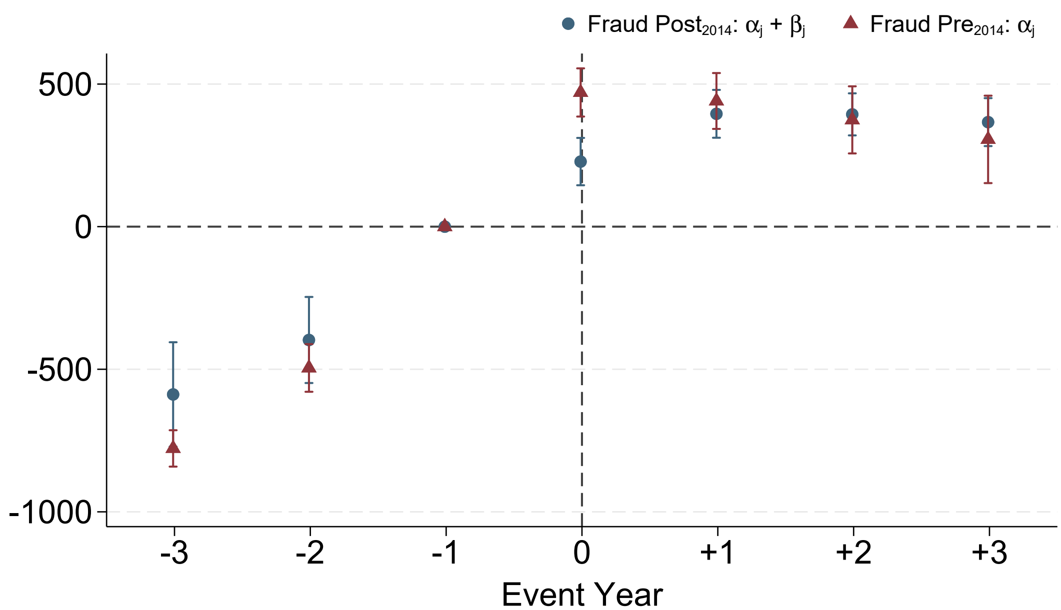
Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is the total number of credit cards.

Figure A.5: Household Response: Balance Amount on Credit Cards ($)

(a) Low Credit Score Consumers



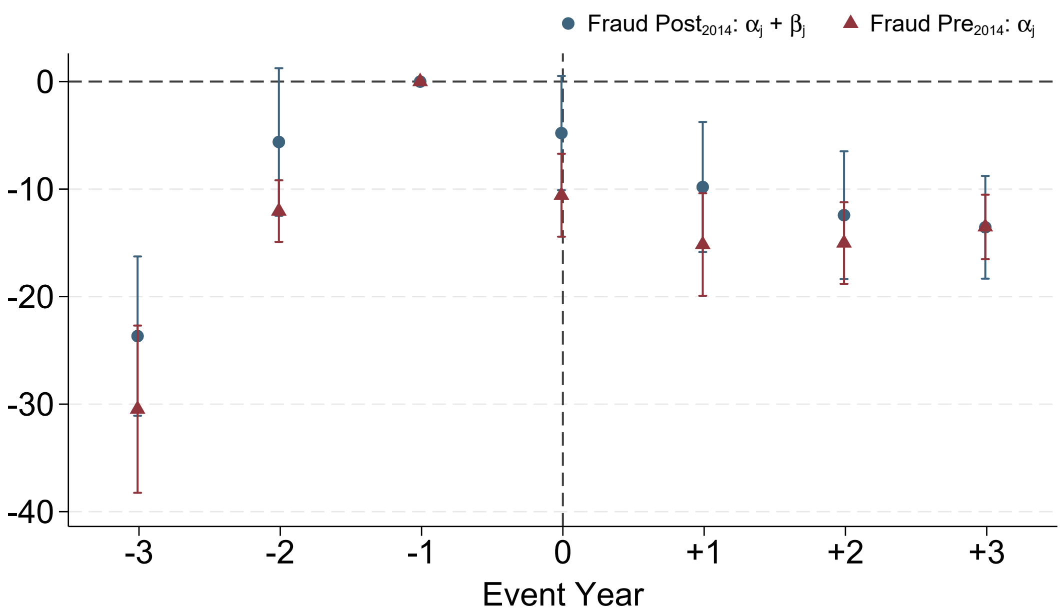
(b) High Credit Score Consumers



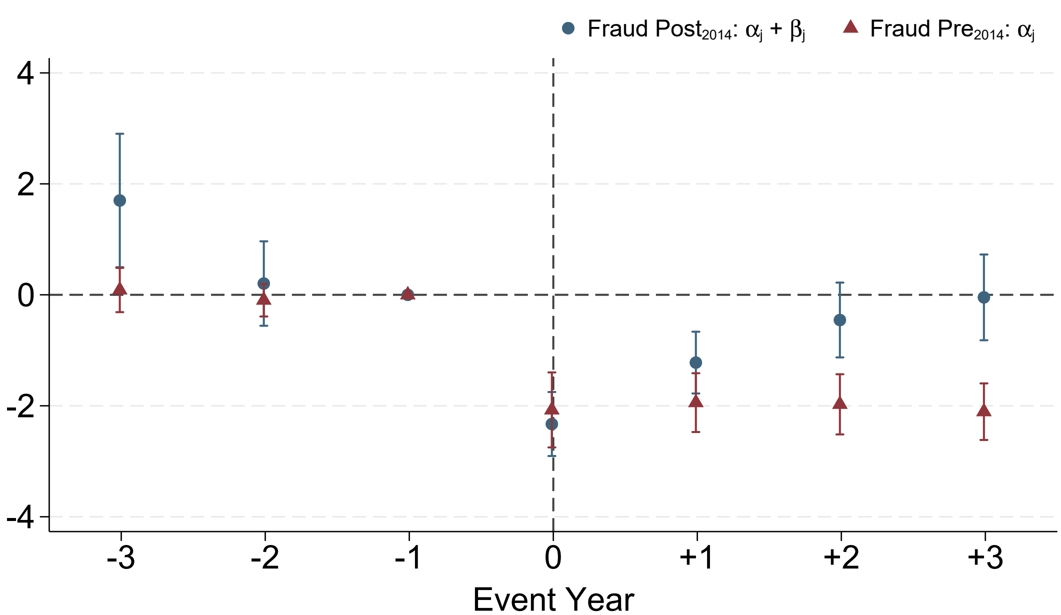
Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is the total balance amount on credit cards.

Figure A.6: Access to Credit: Credit Score

(a) Low Credit Score Consumers



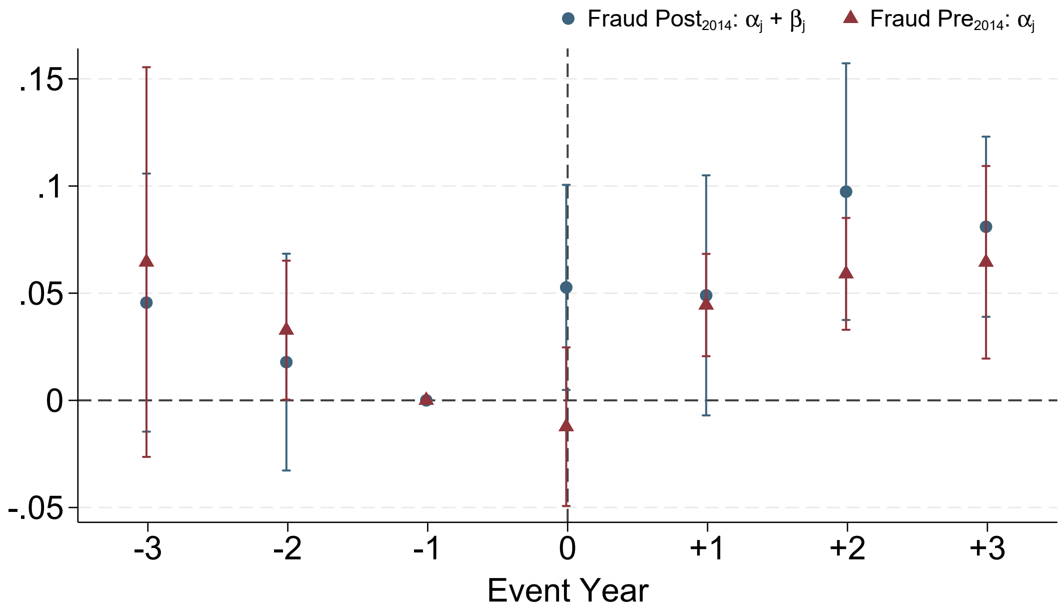
(b) High Credit Score Consumers



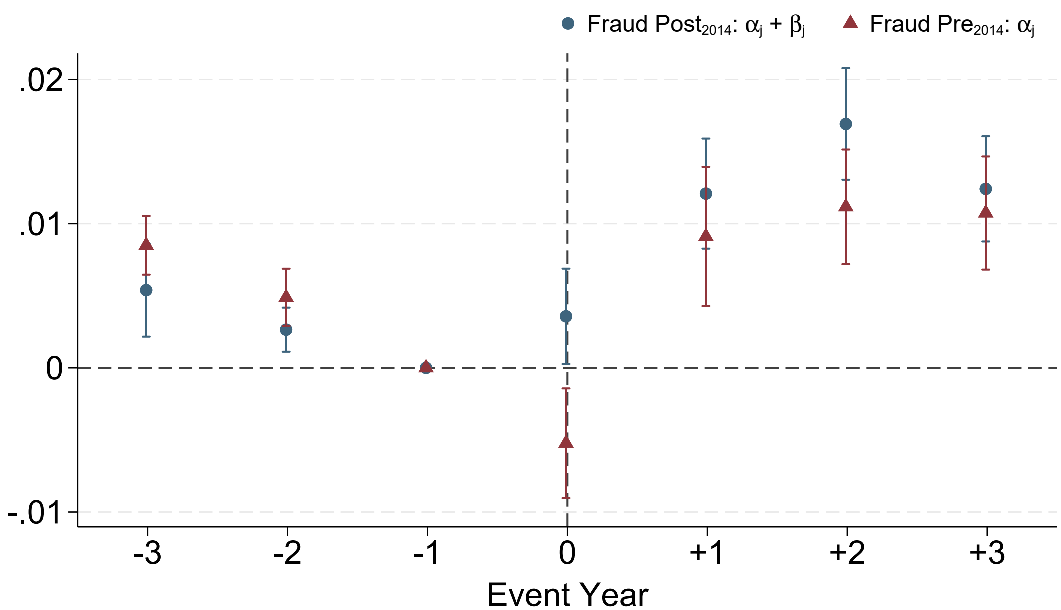
Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is credit score by VantageScore model.

Figure A.7: Household Response: Bankruptcy in Past 7 Years (%)

(a) Low Credit Score Consumers



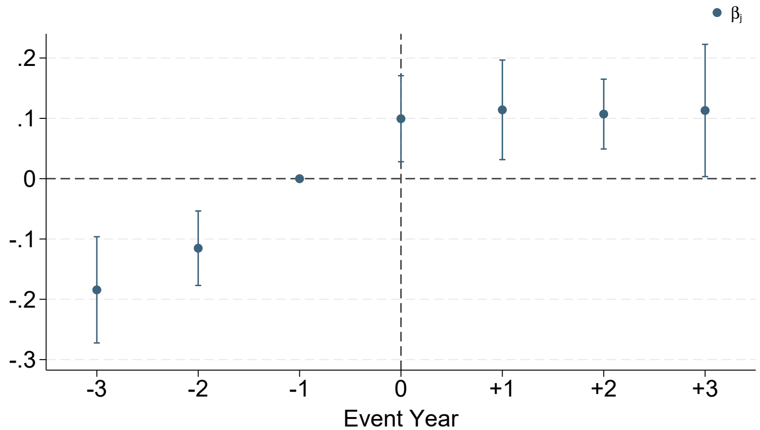
(b) High Credit Score Consumers



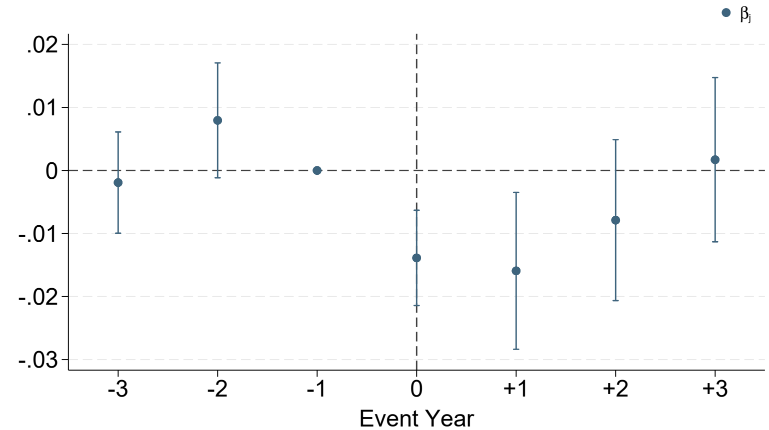
Notes: Panel (a) and (b) show the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from specification 1 for the low credit score and high credit score sub-samples, respectively. The outcome variable is bankruptcy in past 7 years (%).

Figure A.8: Household Response: Credit Demand and Financial Distress, Triple Difference

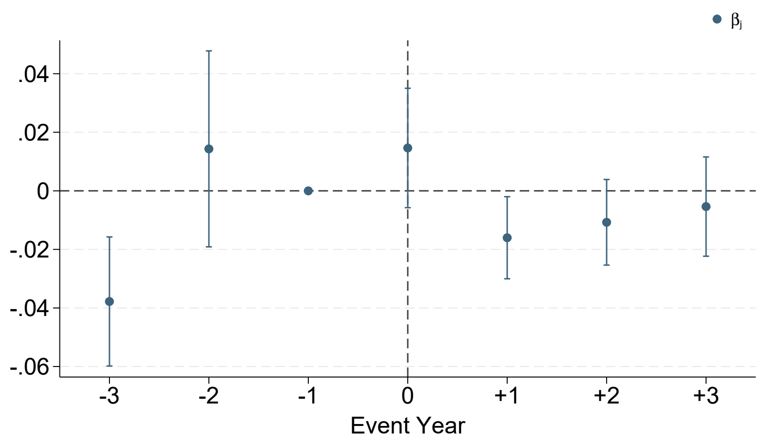
(a) Number of Credit Cards Opened in Past 6 Months



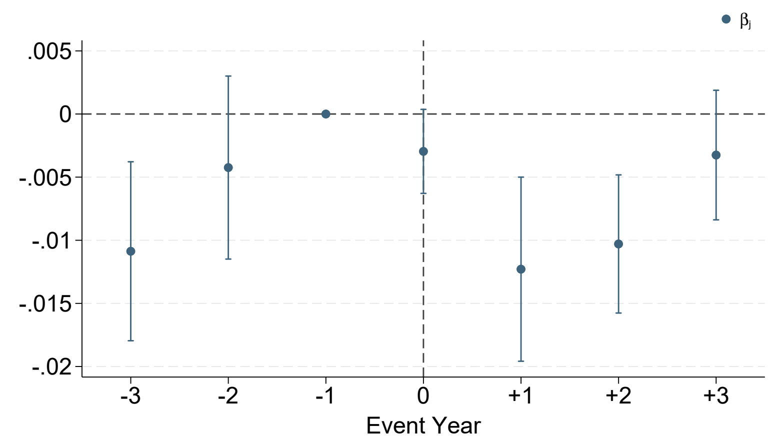
(b) Likelihood of Credit Cards Closure (%)



(c) Number of Credit Card Inquiries in Past 6 Months



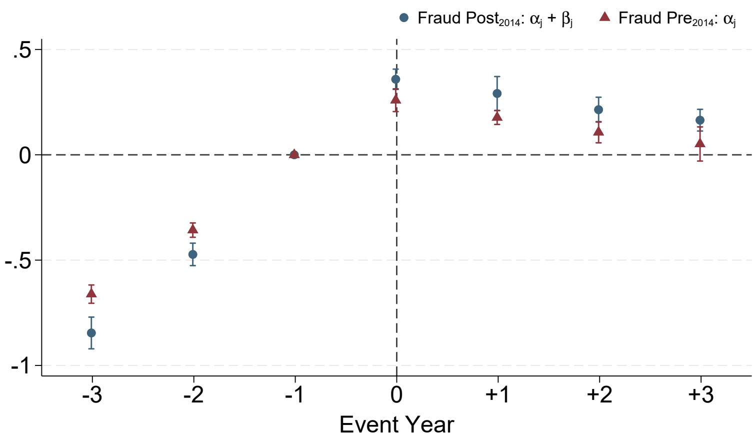
(d) Likelihood of 90+ Days Past Due Credit Cards (%)



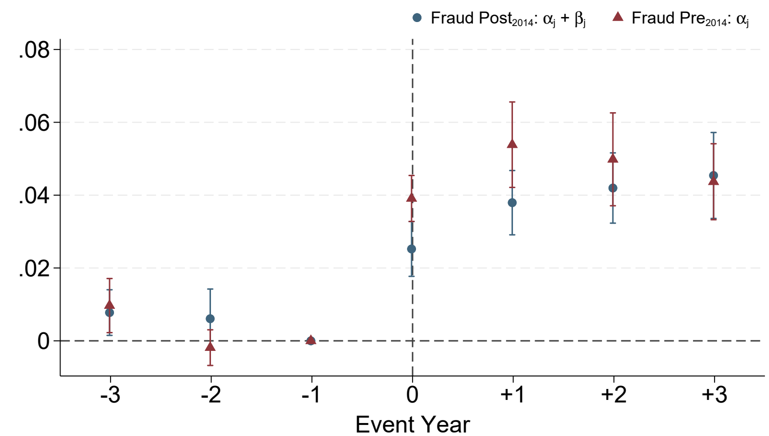
Notes: This figure shows the event study coefficients of the triple difference-in-differences estimation i.e. β_j and 95% confidence interval from our main specification 1 for the full sample.

Figure A.9: Household Response: Credit Demand and Financial Distress, Full Sample

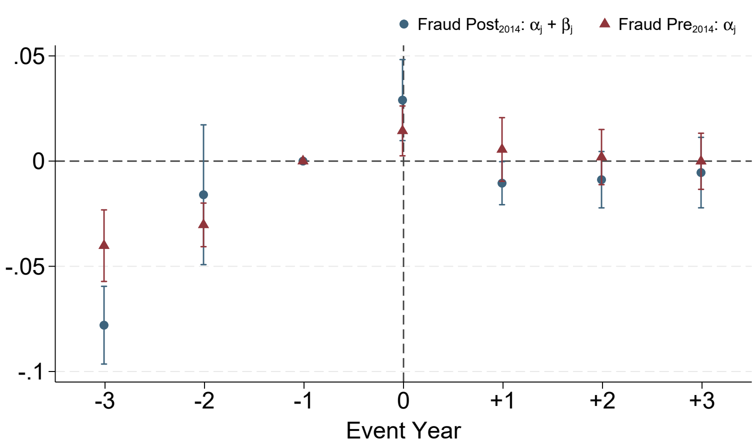
(a) Number of Credit Cards Opened in Past 6 Months



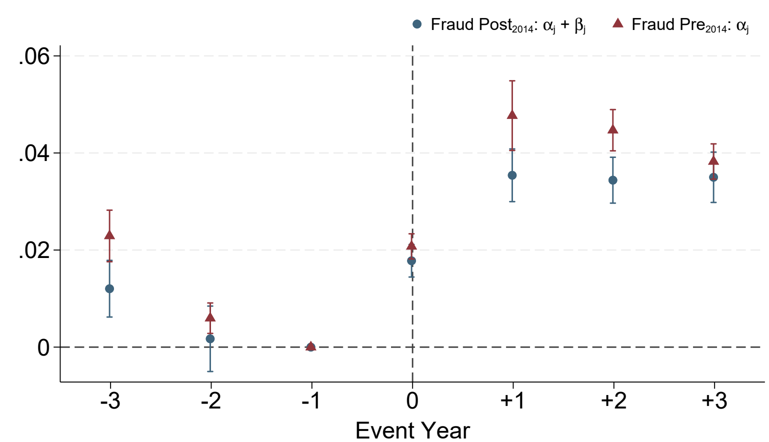
(b) Likelihood of Credit Cards Closure (%)



(c) Number of Credit Card Inquiries in Past 6 Months



(d) Likelihood of 90+ Days Past Due Credit Cards (%)



Notes: This figure shows the event study coefficients of the difference-in-differences estimation i.e. α_j and $\alpha_j + \beta_j$ and 95% confidence interval from our main specification 1 for the full sample.

Table A.1: Summary Statistics for Full Sample, Treated Sample and Control Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All			Treated			Control		
	Mean	St. Dev.	Median	Mean	St. Dev.	Median	Mean	St. Dev.	Median
A. Demographics									
Female (%)	52.06	49.96	100.00	53.24	49.90	100.00	51.59	49.97	100.00
Age (years)	47.61	16.96	47.00	49.40	15.98	49.00	46.85	17.31	46.00
Income ($1,000)	48.00	26.07	41.00	56.65	29.49	49.00	44.63	23.78	38.00
B. Access to Credit									
Credit Score	698.69	97.56	710.00	726.37	90.21	752.00	687.94	98.19	697.00
Credit Limit ($1,000)	31.69	42.47	15.01	50.07	51.37	35.60	24.54	36.01	9.89
Balance Amount on Credit Cards ($1,000)	4.66	10.06	0.87	7.18	12.83	2.48	3.68	8.55	0.44
Balance Amount on Credit Cards 90+ Days Past Due	0.01	0.24	0.00	0.02	0.29	0.00	0.01	0.21	0.00
Credit Card Utilization (%)	20.32	31.22	4.00	22.40	29.72	8.00	19.52	31.75	2.00
Number of Credit Cards	4.35	4.44	3.00	6.43	5.15	5.00	3.55	3.84	2.00
Number of Credit Cards Opened in Past 6 Months	3.54	3.78	2.00	5.17	4.32	4.00	2.91	3.35	2.00
Number of Cards Inquiries in Past 6 Months	0.47	0.82	0.00	0.54	0.86	0.00	0.44	0.80	0.00
C. Financial Distress									
Credit Card Closure (%)	7.72	26.69	0.00	10.90	31.16	0.00	6.48	24.62	0.00
Number of Credit Cards 90+ Days Past Due	0.08	0.57	0.00	0.09	0.65	0.00	0.08	0.54	0.00
Credit Cards 90+ Days Past Due (%)	3.84	19.22	0.00	3.53	18.47	0.00	3.96	19.50	0.00
D. Fraud Experience									
Credit Card Fraud (%)	3.18	17.53	0.00	11.35	31.72	0.00	0.00	0.00	0.00
Observations	29,095,197			8,141,138			20,954,059		

Notes: This table presents summary statistics from the Gies Consumer and Small Business Credit Panel. The statistics are based on data from 2004-2018. The unit of observation is the consumer. The sample is limited to consumers with a non-missing credit score who had at least one credi card account in the smaple period.

Table A.2: Summary Statistics for Matched Treated and Controls

	Treated			Control			T-test	
	Mean	St. Dev.	Median	Mean	St. Dev.	Median	Difference	P-value
Credit Limit ($)	40,246	43,677	27,150	40,216	43,564	27,130	0.23	0.94
Account Balance ($)	5,569	10,464	1,721	5,489	10,099	1,703	0.79	0.27
Credit Score	722	82	739	722	83	740	-0.02	0.54
Observations	316,989			1,584,945				

Notes: The table shows the descriptive statistics of the matched treated vs control borrowers at the year of matching i.e. three years before the fraudulent event. Last two columns report the differences along with p-values of t-test conducted to see the quality of matched treated vs control borrowers.