Opportunistic Borrowing Before Default? A New Test Using Multiple Delinquent Credit Cards

Constantinos Antoniou[*][†], Noah Lyman[‡], Michaela Pagel[§] and Neil Stewart[¶]

May 24, 2025

Abstract

We investigate whether credit card holders borrow opportunistically prior to defaulting on their credit card debt. Our analysis focuses on borrowers who go delinquent on multiple credit cards simultaneously, with some of them eventually being charged off. To control for all unobserved time-variant borrower-specific factors that influence delinquency and default, we then use borrower-by-billing-cycle (year-month) fixed effects. Under strategic default, we expect borrowers to opportunistically utilize available credit on the cards that are eventually charged off, relative to those that are not. Contrary to this expectation, we find that, if anything, users borrow less and repay more on the delinquent cards that are ultimately charged off. These findings suggest that either non-economic factors play a significant role in mitigating opportunistic borrowing in the credit card market or that people are seriously mistaken about the likelihood of their cards being charged off after delinquencies.

Keywords: Credit card delinquencies, credit card borrowing, strategic default
JEL Codes: G5, D14

[*]We thank Andrea Gamba, David Skeie, Brett Green, and seminar participants at Washington University's Olin Business School, Warwick Business School, the DÃŒsseldorf Institute for Competition Economics (DICE), University of Portsmouth and the University of Surrey for helpful comments and suggestions.
[†]Warwick Business School, University of Warwick. Email: Constantinos.Antoniou@wbs.ac.uk
[‡]Warwick Business School, University of Warwick. Email: Noah.Lyman@wbs.ac.uk
[§]Washington University's Olin Business School. Email:mpagel@wustl.edu
[¶]Warwick Business School, University of Warwick. Email:Neil.Stewart@wbs.ac.uk

1 Introduction

Credit card debt is an important liability on households' balance sheets. In the fourth quarter of 2024, more than 1 trillion was outstanding in credit card debt, 3.23% of credit cards were delinquent, and 4. 69% of debt was being charged off. For historical comparison, the delinquency rate peaked in the second quarter of 2009 at 6.77% and 10.54% of debt was charged off at the time.[1] Previous studies have examined whether and in how far credit card default is strategic default by disentangling the effects coming from short-run liquidity shocks vs. long-run strategic incentives, with mixed results. We use a rich and detailed panel of consumers' credit card information to study a new and previously unexplored aspect of strategic default: *opportunistic borrowing* on cards that are expected to be written off.

Opportunistic borrowing occurs when borrowers, anticipating that they may default on a given card, strategically use this card's available credit to maximize their financial benefit before defaulting. Such borrowing allows defaulters to increase current consumption at the expense of credit card providers, who bear the losses. If opportunistic borrowing is indeed prevalent, it has significant implications for both academics who seek to understand the true welfare costs of default, regulators, and credit card providers.

We start our analysis by establishing a key feature of opportunistic borrowing using a two-period model. The model predicts that an opportunistic borrower who realizes they will default in the next period will borrow more of the available credit in the current period, up to the credit card's limit. Thus, once the borrower realizes that they will default, there should be a one-to-one relationship between the amount borrowed and the credit available. Even if opportunistic borrowers are uncertain about whether the card will be ultimately charged-off or not, we would still expect some level of increased borrowing and less repayments for cards that are ultimately charged off relative to cards that are not. Our empirical tests then

[1] See the Delinquency Rate on Credit Card Loans, All Commercial Banks, FRED Economic Data.

examine whether the propensity to borrow (or repay) is higher (or lower) for delinquent cards that are eventually written off (DD cards) compared to delinquent-only cards that are not written off (DO cards).

We use a large sample that records the behavior of more than 1.6 million borrowers over a period of 2 years in the UK, previously used in Gathergood et al. [2019]. In this sample, (roughly) 356 thousand individuals enter delinquency at some point, with approximately 30 thousand of them having their debt eventually written off. Thus, the sample contains a large number of these rare events, which allows us to precisely quantify the dynamics of behavior around delinquency and default.

The main challenge in identifying strategic motives in credit card defaults is the influence of time-varying, borrower-specific factors. For example, borrowers who enter delinquency and eventually default may have higher levels of debt, more volatile income, less savings, or experience more severe income or expense shocks compared to those who enter delinquency but do not eventually default. Additionally, the degree of uncertainty about the likelihood of default and knowledge of the associated costs can vary between borrowers and over time. This uncertainty obstructs the clear identification of strategic default motives when comparing borrowing behavior in DD vs. DO cards between different individuals or even the same individual over time.

To address this identification challenge, we use the fact that in our sample many borrowers default on multiple cards simultaneously (in the same billing cycle) and eventually default on some of them. By focusing on these scenarios, we can include borrower $\times$ billing cycle (year-month) fixed effects to control for all borrower-specific time-variant factors.

The dependent variable in our model is *Net Borrowing*, defined as *Spending* $-$ *Repayment*, in a specific card during a given month. The key independent variables are *Post delinquency*, which equals 1 for the months after a card enters delinquency, *Charged-off*, which equals 1 if this card is a DD card, and *Credit available* on that card. The triple interaction on *Post delinquency* × *Charged-off* × *Credit available* is the key variable of interest that compares behavior across DD and DO cards after delinquency starts. To set a benchmark, we begin with a counterfactual exercise, artificially setting *Net borrowing* equal to *Credit available* for DD cards in the first month after delinquency starts. In this "maxing-out" scenario, the coefficient on the triple interaction is 0.971, which is statistically indistinguishable from 1.

We find no evidence of strategic default in the actual data. In stark contrast to the counterfactual scenario, the actual coefficient on *Credit available* for charged-off cards post delinquency is only 0.012, which strongly rejects the one-to-one relationship between borrowing and credit available predicted by opportunistic borrowing. Moreover, the coefficient on *Post delinquency* × *Charged-off* × *Credit available* is *negative* and statistically significant, showing that the propensity of borrowers to utilize available credit is *lower* in DD cards relative to DO cards. This negative coefficient implies a 57% reduction in the coefficient on *Credit available* after the onset of delinquency for DD cards relative to DO cards. On average, after a DD card enters delinquency, there is £737 of unused credit, approximately 14% of the card's credit limit. Thus, a substantial amount of available credit is left unutilized.

We then explore heterogeneity in strategic borrowing by examining whether the the triple interaction *Post delinquency* × *Charged-off* × *Credit available* varies with borrower characteristics. We first examine whether the level of indebtedness on the card matters and find that if the card's required minimum payment exceeds the median, the triple interaction becomes even more negative. We also investigate whether the triple interaction depends on the borrower's knowledge of the charged-off process. We construct two proxies along these lines, based on the time the borrower has held the card and whether they have experienced a default before. We find that these variables are not associated with a change in the triple interaction. Finally, we find that borrowers with a larger number of cards are more willing to utilize available credit compared to those with a smaller number of cards; however, the coefficient on the triple interaction for the former group remains negative.

To further explore heterogeneity we estimate the model using quantile regression techniques, which are used to estimate specific points on the conditional distribution of an outcome variable. Such models enable us to explore the heterogeneity in strategic behavior among individuals placed at different levels within the distribution of *Net borrowing* in our sample. We find that the coefficient on *Post delinquency* × *Charged-off* × *Credit available* is negative and statistically significant in all the quantiles we consider, which indicates that this relationship is present in the entire distribution and is not driven by particular segments of the population.

We also estimate a clean controls version of the baseline model, following recent developments in the analysis of staggered treatments across time periods [see, e.g., the review in Freedman et al., 2023]. Specifically, we use a clean-control estimating procedure where we create one stack for each delinquency event using only clean controls, i.e., borrowers, who were not holding cards that were charged off over the sample period. Our conclusions regarding opportunistic borrowing remain unchanged with the clean-controls model: the coefficient on credit available for charged off cards post delinquency is an order of magnitude less than 1 (0.013), and the coefficient on the triple interaction *Post delinquency* × *Charged-off* × *Credit available* is negative and statistically significant.

Our model thus far compares behavior in DD and DO cards within a borrower and month, but without taking into account the exact month when these cards entered delinquency. In an additional test, we introduce a case identifier for borrowers who enter delinquency on multiple cards within the same month, some of which ultimately default.

We continue to find no evidence supporting opportunistic borrowing. The propensity to borrow available credit drops equally post-delinquency for both DD and DO cards that enter delinquency in the same month some of which are charged off. Moreover, there is no difference in the reduction in credit utilization for DD cards that enter delinquency in the same month as other DO cards, and for DD cards that enter delinquency on their own, which again indicates that DD cards that are part of a multiple delinquency event are not treated differently by borrowers.

We answer four additional open questions. First, are the borrowers who go delinquent on multiple cards simultaneously (and some of which they default on) different from other borrowers that default? Second, can borrowers predict which card they default on? Third, is it helpful to default in the sense that credit is available on the cards that are eventually charged off? And finally, are default costs unaffected by the amount the user defaulted upon?

To answer the first open question, we examine how different our borrowers in question are to the whole population of borrowers that go delinquent and default on credit cards. Regarding the second question, we conduct predictability regressions using card-specific information, such as minimum payment amounts, up to the point of delinquency to assess how well we can predict which cards will eventually default. As for the third open question, as already mentioned, we document that roughly 0.15×4.8K=£721 could be borrowed opportunistically.

As for the final open question, we explore whether the costs of defaulting on credit card debt are sensitive to the amount defaulted. This is an important question when thinking about opportunistic borrowing because, if default costs rise in proportion with the amount defaulted, then incentives to borrow opportunistically are reduced. We analyze a variable in our dataset that corresponds to borrowers' credit scores, referred to as the *Charged-off rate*.[2] We find that although defaulting on a card raises a borrower's *Charged-off rate* for other cards, the amount defaulted does not materially exacerbate this. Thus, the explanation that opportunistic borrowing does not occur because of potentially higher additional default costs

[2] This variable is a probability that a borrower in that particular risk band will default. We describe the variable in detail later in the paper.

is not supported by the data. Beyond the *Charged-off rate*, we also show that APRs and credit limits on other cards are not affected by the amount defaulted.

The next section reviews the relevant literature and highlights our contribution. Section 2 presents a simple model that illustrates the opportunistic borrowing hypothesis. Section 3 describes the data, Section 3.3 the econometric analysis, and Section 4 presents our findings. Finally, Section 5 concludes the paper.

1.1 Literature Review

An important issue in debt markets is to understand the nature and extent of strategic defaults. Several studies have examined different settings to understand whether defaults are driven by contemporaneous liquidity shocks (non-strategic default) or by high future interest payments (strategic default).

In the mortgage market, Mayer, Morrison, Piskorski, and Gupta [2014] and Haughwout, Okah, and Tracy [2016] analyze the impact of mortgage modification programs. They show that the changes to delinquency and default rates in response to the programs are consistent with consumers defaulting strategically. Opposing views come from Scharlemann and Shore [2016], Ganong and Noel [2020], Indarte [2020], and Ganong and Noel [2023], who show that the principal driver of mortgage defaults is adverse liquidity shocks, as opposed to long-term strategic considerations. Another study, Gerardi, Herkenhoff, Ohanian, and Willen [2018], finds that both liquidity and strategic considerations play a role in default decisions.

In terms of credit cards, Dobbie and Song [2020] use a large-scale field experiment to investigate the impact that immediate payment reductions and delayed interest write-downs have on default. The authors show that delayed interest write-downs led to a significant reduction in default rates early on in the program, which suggests a reduction in the incentive for borrowers to default strategically.

In earlier work, Fay, Hurst, and White [2002] use retrospective questions about past defaults in a survey conducted by the Panel of Income Studies (PSID) in 1996 to examine if default is strategic. They find that households are more likely to file for bankruptcy when the value of the debt that stands to be written off is larger, consistent with strategic incentives. Agarwal, Liu, and Mielnicki [2003] model the probability of default as a function of the location of different borrowers. They show that controlling for personal characteristics, default is more likely in districts with more generous homestead and property exemption laws. Gross and Souleles [2002] use a large sample of account-level data and model the demand for unsecured debt and its impact on delinquency and bankruptcy. They show that various macro-economic and individual factors influence the probability of default, but conclude that, even after accounting for all these factors, the probability of default goes up by one percentage point between 1995 and 1997, an increase which they attribute to a decline in the social stigma associated with default.

Our work contributes to the literature by testing for strategic borrowing behavior in a new setting: borrowers who enter delinquency on multiple credit cards, some of which are eventually charged-off. The strategic default hypothesis posits that borrowers will borrow to max-out cards that are eventually charged-off. By focusing on borrowers with several cards, we can control for the effect of unobserved, time-varying, borrower-specific factors that influence their decisions, and study strategic default motives by comparing the borrowing behavior of the same borrower in the same month across cards that become delinquent only vs. cards that become delinquent and eventually default. We find no evidence of opportunistic borrowing, suggesting that non-economic factors may be discouraging strategic default in the credit card market.

A study that documents the importance of non-economic factors in strategic default decisions on credit cards is by Bursztyn et al. [2019], who designed a natural experiment to test whether treated borrowers who receive a test message stating that is an "injustice" to default on debt when you are able to repay default less. Their results confirm the hypothesis, highlighting that fairness considerations towards debt providers are important in strategic default decisions. Our findings are in line with the analysis in Bursztyn et al. [2019], as borrowers do not seem to be defaulting strategically at the expense of credit card providers.

2 A Model of Opportunistic Borrowing Before Default

In this section, we use a simple model to illustrate the hypothesis of our main test. Specifically, we hypothesize that a forward-looking agent who decides to default in the next period should increase borrowing in the current period up to the limit of the credit card instead of repaying it.

We consider a two-period model. In period zero, there is no income; the agent borrows to smooth consumption, given the expected income in the second period. The agent then enters the first period with some debt, and some income realization. If the income is low, the agent goes delinquent for one period and then either repays their debt (plus a pecuniary cost) or defaults in period 2. The agent's consumption utility is characterized by a log function.

More formally, we have two periods, one consumption good, log utility, the agent consumes in periods 1 and 2, denoted by c_1 and c_2, enters period 1 with debt $b_1 > 0$, may go delinquent or roll-over and borrow more in period 1, $b_2 > 0$. They also face a credit limit in period 1, $\bar{b}$.

Suppose the agent does not go delinquent, repays their debt entirely, their credit limit is not binding, and they enter period 1 with some debt, then $b_2 = (1+r)b_1 + c_1 - y_1 < \bar{b}$ In turn, the optimal solution for consumption in period 1, denoted by c_1^*, is

$$0 < (1+r)b_1 + c_1 - y_1 < \bar{b} \text{ and } max\{log(c_1) + \delta log(y_2 - (1+r)((1+r)b_1 + c_1 - y_1))\}$$

which gives

$$\frac{1}{c_1} = \delta \frac{1}{y_2 - (1+r)((1+r)b_1 + c_1 - y_1)} \Rightarrow c_1 = \frac{1}{\delta}(y_2 + y_1(1+r) - c_1(1+r) - (1+r)^2 b_1)$$
$$\Rightarrow c_1^* = \frac{\delta}{1+r+\delta}(y_2 + y_1(1+r) - (1+r)^2 b_1)$$

Suppose the agent goes delinquent in period 1 (and pays a late fee p), ultimately repays his debt entirely in period 2, and their credit limit is not binding, then $b_2 = (1+r)b_1 + p + c_1 - y_1 < \bar{b}$.

The optimal solution for c_1^* is

$$0 < (1+r)b_1 + c_1 - y_1 < \bar{b} \text{ and } max\{log(c_1) + \delta log(y_2 - (1+r)((1+r)b_1 + p + c_1 - y_1))\}$$

which gives

$$\frac{1}{c_1} = \delta \frac{1}{y_2 - (1+r)((1+r)b_1 + p + c_1 - y_1)}$$
$$\Rightarrow c_1 = \frac{1}{\delta}(y_2 + y_1(1+r) - c_1(1+r) - (1+r)^2 b_1 - (1+r)p)$$
$$\Rightarrow c_1^* = \frac{1}{1+r+\delta}(y_2 + y_1(1+r) - (1+r)^2 b_1 - (1+r)p)$$

The agent goes delinquent and pays the penalty p because they do not have enough income in period 1, y_1 to pay the minimum payment.

Finally, suppose that the agent goes delinquent in period 1 and defaults in period 2 (and pays the pecuniary cost c). In this case, the agent will opportunistically borrow up to the limit and $b_2 = \bar{b} = (1+r)b_1 + p + c_1 - y_1$, which determines c_1^*. In turn, their utility is:

$$\text{if } c_1^* = \bar{b} - (1+r)b_1 - p + y_1 \text{ utility is then } log(c_1) + \delta log(y_2 - c))$$

Proposition. *Comparative Statics:*

- ***If delinquent without default:*** $\frac{\delta c_1}{\delta b} = 0$ *(agent's consumption is independent of their borrowing limit),* $\frac{\delta c_1}{\delta y_{1,y2}} > 0$ *(consumption is increasing in income), and* $\frac{\delta c_1}{\delta b_1} < 0$ *(consumption is decreasing in initial debt)*

- ***If delinquent with default:*** $\frac{\delta c_1}{\delta b} = 1$ *(agent's consumption increases one-to-one with borrowing limit),* $\frac{\delta c_1}{\delta y_1} > 0$ *(consumption is increasing in income) and* $\frac{\delta c_1}{\delta b_1} < 0$ *(consumption is decreasing in initial debt)*

The distinguishing prediction here is that when the agent goes delinquent and expects to default, they borrow opportunistically and their consumption is fully determined by their borrowing limit, which is not the case if the agent goes delinquent but does not expect to default.

3 Empirical Methods

3.1 Sample construction

Our data come from the Argus Information and Advisory Services' Credit Card Payments Study (CCPS). The CCPS has detailed information on contract terms and billing records from five major credit card providers in the United Kingdom, who have a combined market share of over 40 percent. Our dataset contains monthly observations on each individual from January 2013 to December 2014 for a 10 percent randomly selected representative sample of individuals in the CCPS database who held a credit card with at least 1 of the 5 issuers. For more information on the dataset, see Gathergood, Mahoney, Stewart, and Weber [2019].

The initial sample contains 2,190,216 borrowers, 0.95% of which experience default. Thus, in line with previous studies, defaults are quite rare among borrowers. To focus the analysis on borrowers who are financially stressed, we retain in our sample individuals who hold multiple cards and go delinquent on more than one card during the sample period. We classify an individual as delinquent on a card in month t if the variable cycles delinquent (CD) (which counts the number of months that the individual has failed to make the minimum payment as of that month for that card) satisfies $CD_{t-1} = 0$, $CD_t > 0$ and $CD_{t+1} > 0$.[3] We drop from our sample cards that become charged off without going delinquent, as these are probably canceled at the request of the borrower. We also remove cards that start off in the sample as delinquent. Our final sample contains 7,054 borrowers who hold 16,133 cards, 6,793 of which are eventually charged-off.

3.2 Summary Statistics

Table 1 displays summary statistics for our main sample. All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles.

Total spending is £146.5 and *Discretionary spending* (which excludes charges and fees) is on average £96.61 per month. Average *Repayment* is 108.7 and average *Net borrowing* (calculated as $\textit{Discretionary spending}_t - \textit{Repayment}_t$) is -10.88. This finding is somewhat surprising as it shows that, on average, the financially stressed borrowers in our sample pay more money into their cards relative to how much they borrow.

The average credit limit is £4,807.7, and the average APR is 22.3%. *Utilization* ($\frac{ClosingBalance_t}{\textit{Credit Limit}_t}$) is on average 74.7%, which implies a £1,231.3 of *Credit Available* on each card ($CreditLimit_t - OpeningBalance_t - ChargesFees_t$).[4] *Net utilization* ($\frac{\textit{Net borrowing}_t}{\textit{Credit available}_t}$) is on average -25.4%,

[3] We use two consecutive months with cycles delinquent being positive in order to avoid cases where borrowers just forget to make their payment in a month. Thus, to increase the chances that we identify "true" delinquency events, we require two consecutive months with cycles delinquent being non-zero.

[4] We find that in several cases borrowing does exceed the credit limit, pushing *Utilization* above 1. It is up to the discretion of the lender to allow borrowing beyond the credit limit. In our estimations, we set

which indicates that spending is less than repayment. On average, borrowers roll over a substantial amount of debt (£2,469.1) and thus pay significant monthly fees (£49.9). On average, in the whole sample, borrowers are 1.47 months delinquent. Figure 1 shows the number of months that charged-off cards are delinquent. The vast majority of cards are charged off after being delinquent for seven months.

In the next section, we describe the econometric model we use to test the hypothesis of opportunistic borrowing.

3.3 Model specification

Our main regression specification is as follows:

$$\begin{aligned}
\textit{Net Borrowing}_{i,j,t} = {} & \beta_0 \textit{Credit available}_{i,j,t} + \beta_1 \textit{Charged-off card}_{i,j} \times \textit{Credit available}_{i,j,t} \\
& + \beta_2 \textit{1-3 months before delinquency}_{i,t} \times \textit{Credit available}_{i,j,t} \\
& + \beta_3 \textit{1-3 months before delinquency}_{i,t} \times \textit{Charged-off card}_{i,j} \times \textit{Credit available}_{i,j,t} \\
& + \beta_4 \textit{0-6 months after delinquency}_{i,t} \times \textit{Credit available}_{i,j,t} \\
& + \beta_5 \textit{0-6 months after delinquency}_{i,t} \times \textit{Charged-off card}_{i,j} \times \textit{Credit available}_{i,j,t} \\
& + \beta_6 \textit{More than 6 months after delinquency}_{i,t} \times \textit{Credit available}_{i,j,t} \\
& + \beta_7 \textit{More than 6 months after del}_{i,t} \times \textit{Charged-off card}_{i,j} \times \textit{Credit available}_{i,j,t} \\
& + \zeta^\top \mathbf{X} + \alpha_{i,t} + \varepsilon_{i,j,t} \qquad (1)
\end{aligned}$$

The outcome variable $\textit{Net Borrowing}_{i,j,t}$ is the difference in discretionary borrowing minus repayments by individual i for card j in month t. Discretionary borrowing is total borrowing on card j by i during month t minus charges and fees paid on card j by i during t. $\textit{Credit available}_{i,j,t}$ is calculated as $\textit{Credit Limit}_{i,j,t} - \textit{Charges and fees}_{i,j,t} -$

Credit Available to zero when this happens.

Beginning balance$_{i,j,t}$, i.e., the credit limit on card j owned by i in month t, the fees paid for card j during month t, and j's balance at the start of month t. *1-3 months before delinquency*$_{i,t}$ is an indicator variable set to 1 if month t is in the three-month period prior to the beginning of delinquency for borrower i, i.e., from $t-3$ to $t-1$, where $t=0$ marks the start of delinquency. *0-6 months after delinquency*$_{i,t}$ is a similar indicator that flags the 7-month period after the start of the delinquency ($t=0$ to $t+6$). *More than 6 months after delinquency*$_{i,t}$ is a similar indicator that equals to 1 for all the months after $t+6$. The omitted category is the months prior to $t-3$. *Charged off card*$_{i,j}$ is an indicator that flags whether card j is a DD card, i.e., one that is ultimately charged off by the credit card provider. $\mathbf{X}$ is a vector that includes all the other interactions of these variables that are not explicitly shown in Equation 1, and $\alpha_{i,t}$ is an individual $\times$ year-month fixed effect. Standard errors in all our models are clustered at the individual and year-month levels.

We separate the period after delinquency into *0-6 months after delinquency* and *More than 6 months after delinquency* as we expect that the strategic borrowing should happen as soon as delinquency starts on the card that is destined for default (and so during the *Post delinquency* period). If a strategic borrower who aims to max-out the card that will eventually default delays the borrowing too much, they risk the card being charged-off by the provider before they have an opportunity to borrow the additional funds.

Under opportunistic borrowing, our model predicts that there should be a one-to-one relationship between *Net borrowing* and *Credit available*, when the user expects to default. Thus, cards that are eventually charged off should be utilized more once delinquency begins. A reduced-form test of this hypothesis is that the coefficient on *Credit available* goes to 1 when delinquency starts for DD cards that are charged off, i.e., $\beta_0 + \beta_1 + \beta_4 + \beta_5 = 1$. Even if maxing-out the eventually charged-off card does not occur (because, for example, there is some uncertainty on whether the card will be charged off), opportunistic borrowing implies that the individual utilizes more of the available credit on this DD card relative to other DO cards that are not destined for charged off. Thus, a weaker form of opportunistic borrowing is $\beta_5 > 0$.

The opportunistic borrowing hypothesis does not make concrete predictions on how individuals utilize credit available on DD cards in the *1-3 months before delinquency* or *More than 6 months after delinquency* periods.

As we discussed earlier, the conditions that we require for the occurrence of a delinquency and default event coupled with the individual $\times$ year-month fixed effect ensure that the coefficients on the interactions between *Credit available*, *Charged-off card* and the timing indicators are estimated using variation in the type of card (DD vs. DO) within borrowers who are delinquent in multiple cards in a given month. The coefficient on *Credit available* is the reference category in the model, which is estimated using variation from the months before $t-3$.

4 Results

4.1 Baseline Analysis

Table 2 shows the results when estimating Equation 1. We start the analysis by estimating the model in hypothetically generated data where individuals max-out the cards that are eventually charged off. To do this, we set *Net borrowing* equal to *Credit available* in the first month of the *Post delinquency* period and then set both these variables to zero thereafter. The estimation results of our model in the generated data are presented in Column (1).

The coefficient on *Credit available* for the reference category is 0.055 and statistically significant. This is a relatively low estimate, indicating a borrowing of 5.5 pence per month for each additional pound of available credit in the 6-month period after delinquency compared to the period before delinquency. In this hypothetical scenario of opportunistic borrowing, the coefficient *Post delinquency* × *Charged-off card* × *Credit available* is 0.971, indicating that maxing out implies an enormous increase in the sensitivity of *Net borrowing* to *Credit available* for DD after delinquency. The bottom row is the coefficient on *Credit available* post delinquency for DD, which, in this "maxing-out" scenario, is equal to 1.

The actual results are shown in Column (2) of Table 2. The coefficients on *Credit available* for the reference category, and its interactions with *Charged-off card* and *1-3 months before delinquency* are the same as in Column (1) (which is expected as for that part of the sample nothing has changed). In stark contrast to the hypothetical maxing-out results from Column (1), the coefficient on *0-6 months after delinquency* × *Charged-off card* × *Credit available* is -0.017 and statistically significant at the 1% level, indicating a 57% reduction in the propensity to use available credit for DD cards relative to DO cards after delinquency starts.

In unreported results, we find that the coefficient on *More than 6 months after delinquency* × *Charged-off card* × *Credit available* is also negative and statistically significant at the 1% significance level, equal to -0.027, marking a further reduction in the propensity of borrowers to utilize credit for DD cards relative to DO cards after delinquency. This finding is also inconsistent with strategic behavior.

Overall, the findings in this section do not lend any support to the opportunistic borrowing hypothesis. In fact, the results seem to be pointing in the opposite direction—after going delinquent, individuals are much less willing to borrow available credit for cards that are eventually charged-off relative to cards that are not charged-off.

4.2 Cross-sectional heterogeneity

In this section we examine whether the propensity to use available credit for DD vs. DO cards after delinquency depends on various borrower and card characteristics.

Our first three sorting variables measure how indebted a borrower is on a given card. To conduct this test we set the indicator *Group interaction* to 1 if the utilization, revolving balance or minimum payment of the specific card in month t is above the sample median. We interact this indicator with *0-6 months after delinquency* $\times$ *Charged-off card* $\times$ *Credit available* to examine if borrowing propensity depends on the level of indebtedness.

The results, shown in Table 3, show that the interaction *0-6 months after delinquency* $\times$ *Charged-off card* $\times$ *Group interaction*$\times$ *Credit available* is insignificant in Columns (1) and (2), and negative and significant in Column (3). This indicates that the propensity to use available credit after delinquency for a DD card is lower if this card has a high minimum payment.

The incentives to max-out a DD card may be weaker if the borrower has a limited understanding of the charge-off process. For example, if they believe that the credit card company will not charge-off their cards, even after many cycles delinquent, then they may be more reluctant to borrow strategically. We construct two variables that may relate to this uncertainty: the time that the borrower has held the card and whether they experienced a default episode before on another card. Borrowers who held their card for a longer period (and have thus had more interactions with the credit card company), or borrowers who experienced a charge-off episode before, may face less uncertainty about the charge-off process. The results in Columns (4) and (5) indicate that the coefficient on *0-6 months after delinquency* $\times$ *Charged-off card* $\times$ *Group interaction*$\times$ *Credit available* is insignificant.

In Column (6) we define the indicator *Group interaction* based on the number of credit cards held by a borrower. It is possible that borrowers with many cards are more strategic in that they obtain more cards in anticipation that they would max-out some of them if they ever run into financial problems. In line with this idea, we observe that the coefficient on *0-6 months after delinquency* $\times$ *Charged-off card* $\times$ *Group interaction*$\times$ *Credit available* is positive and significant, equal to 0.014, indicating a higher propensity to borrow available credit on DD cards after delinquency if the borrower has an above median number of credit cards. The baseline coefficient (i.e., for borrowers with a below median number of credit cards) is -0.022, thus the net effect for these borrowers with many cards is still negative.

4.3 Quantile regressions

In this section, we estimate quantile regression models, estimating specific points of the conditional distribution of *Net borrowing*. In a quantile regression of $y_{j,t}$ on $x_{j,t}$, the slope coefficient β_τ is chosen to minimize the quantile weighted absolute value of errors, where τ indicates the specific quantile. So, through the variation of τ, quantile regression models enable us to explore the heterogeneity in borrowing behavior among individuals placed at different levels of *Net borrowing* in our sample.

The results are shown in Table 4. We observe that the coefficient on *Credit available* increases with the modeled quantile, indicating that borrowers in the upper ends of the net borrowing distribution are more willing to borrow available credit.

The coefficient on *0-6 months after delinquency* $\times$ *Credit available* is negative and significant, becoming even more negative with the modeled quantile. This suggests that people in the upper ends of the distribution of *Net borrowing* are less willing to use available credit for DO cards. The coefficient on *0-6 months after delinquency* $\times$ *Charged-off card* $\times$ *Credit available* is negative and significant, becoming even more negative with the modeled quantile. This shows that the borrowers with higher *Net borrowing* are even less willing to use available credit for DD cards.

4.4 Clean controls

We also estimate a "clean controls" version of the model, following the analyses in recent papers that consider settings in which treatments are staggered in adoption and vary with time [see, e.g., the review in Freedman et al., 2023]. Specifically, we use a clean-control estimating procedure where we create one stack for each treatment (a month in which a borrower goes into delinquency) using only clean controls, i.e., individuals that were not holding cards that were charged off over the sample period. The results are very similar and can be found in Table 5.

4.5 Aligning the timing of delinquencies

In this section we conduct a test that identifies DD and DO cards that enter delinquency in the same month. For this test, we define month t as the start of a delinquency event if in that month the borrower goes delinquent in $N_D > 1$ cards with $N_C < N_D$ cards ultimately charged off. We also require that the borrower did not have another card charged-off before month t. A sub-sample of 665 of these borrowers holding 1,609 cards that experience such a delinquency event. We flag these cards by setting the indicator *Delinquencies of* $N > 1$ *cards and* $N > n > 1$ *charged off* equal to 1.

First, we examine whether the delinquent borrowers who meet these additional criteria differ from those in our overall sample. The results of a randomization check are presented in Table 6. Clearly, the selection of individuals who simultaneously go delinquent on multiple cards is not random. That said, while all observed differences are statistically significant, we argue that they are not economically substantial.

The results from the main test are shown in Table 7. We continue to find no evidence supporting strategic default on credit card debt. The coefficient on *0-6 months after delinquency* × *Charged-off card* × *Credit available* is negative and statistically significant at the 1% significance level, equal to -0.016. The coefficient on *0-6 months after delinquency* × *Charged-off card* × *Delinquencies of* $N > 1$ *cards and* $N > n > 1$ *charged off* × *Credit available* is statistically insignificant, showing no difference in the propensity of borrowers to use available credit for DD cards that are part of a multiple delinquency event relative to DD cards that are not. Moreover, the coefficient on *0-6 months after delinquency* × *Delinquencies of* $N > 1$ *cards and* $N > n > 1$ *charged off* × *Credit available*, which shows the change in the propensity to use credit for DO cards that are part of the multiple delinquency event is negative and significant. Moreover, the coefficient on *0-6 months after delinquency* × *Charged-off card* × *Delinquencies of* $N > 1$ *cards and* $N > n > 1$ *charged off* × *Credit available* is statistically insignificant indicates that there us no change in behavior for DO vs DD cards in a multiple delinquency event. So, when such multiple delinquency events take place, borrowers reduce their propensity to use up credit for both DO and DD cards equally. Overall these findings suggest that our conclusions remain intact when testing the hypothesis in a model that aligns the timing of delinquencies across DD and DO cards.

4.6 Credit card outcomes around delinquency time

In this section we analyze various credit card outcomes around delinquency events for DD and DO cards. The results are shown in Table 8. In Column (1) the dependent variable is *Total spending*. The coefficient on *0-6 months after delinquency* is negative and significant, so *Total spending* reduces after delinquency starts. The coefficient on the interaction *0-6 months after delinquency* × *Charged-off card* is insignificant, thus there is no difference in *Total spending* between DO and DD cards.

In Column (2) the dependent variable is *Discretionary spending* (which excludes *Charges and fees*). The coefficient on *0-6 months after delinquency* is negative and significant, and larger compared to Column (1). Again there is no difference after delinquency between DO and DD cards.

In Column (3) the dependent variable is *Repayment*. The coefficient on *0-6 months after delinquency* is negative and significant, which implies that after delinquency starts, the borrower repays less, which is in line with a negative income shock. This reduction is stronger for DD cards, as the coefficient on the interaction *0-6 months after delinquency* $\times$ *Charged-off card* is negative and significant.

In Column (3) the dependent variable is *Net borrowing*. The coefficient on *0-6 months after delinquency* is negative and significant, but the coefficient on the interaction *0-6 months after delinquency* $\times$ *Charged-off card* is positive and significant (and roughly equal in absolute value at 20.26 vs -19.12). This means that *Net borrowing* drops for DO cards after delinquency starts, but remains roughly constant for DC cards. *Utilization* and *Net utilization* increase for both DO and DD cards, and more so for the latter.

On the whole, spending and repayment drop for both DO and DD cards after delinquency. However, because repayment drops more than spending, *Net borrowing, Utilization and Net utilization* increase more for DD cards relative to DO cards after delinquency starts. These results are not in line with opportunistic borrowing, in the sense that spending actually drops after delinquency. The increase in card usage is driven by a reduction in repayment, which is in line with negative income shocks as the underlying reason for the delinquency.

In Table 9, we repeat the same tests by examining if the results differ when the delinquency dates around DO and DD cards are aligned (as in Table 7). As shown in Column (4), we find that the coefficient on *0-6 months after delinquency* is negative and significant, indicating a reduction in *Net borrowing* for DO cards. The coefficient on *0-6 months after delinquency*$\times$

Delinquencies of $N > 1$ cards and $N > n > 1$ charged off, which shows the change when the DO cards are part of an "event" (as described in Section 4.5), is positive but insignificant, indicating no incremental change in *Net borrowing* for DO cards that are part of an event. The coefficient on *0-6 months after delinquency* $\times$ *Charged-off card* $\times$ *Delinquencies of $N > 1$ cards and $N > n > 1$ charged off* is negative and significant, indicating that *Net borrowing* after delinquency reduces for DD cards that part of an event relative to DO cards that part of the event (Columns (5) and (6) show a similar effect for *Utilization* and *Net utilization*). Thus, when we align delinquency time for DO and DD cards, we see a reduction in usage for DD relative DO cards after delinquency. This result is not in line with opportunistic borrowing.

Figure 2 shows the predicted margins for *Net borrowing* (Panel A), *Net utilization* (Panel B), *Repaynent* (Panel C), and *Utilization* (Panel D) for the four types of cards (DO vs DD for event and non-event) over time around delinquency. When comparing the DD versus DO cards for events (orange vs. green dots), we see that there is no difference in net borrowing or repayment. When comparing the blue dots (DD, non-event) with the red dots (DO, non-event) we see a higher predicted *Utilization* for the blue dots. However, we do not see a strong upward trend for the blue dots after delinquency, with *Utilization* stabilizing at around 85%. This suggests that a significant amount of available credit is left unutilized for DD cards. We find much more similar behavior for DO and DD event cards for events (orange vs. green dots); a decreasing trend over time after delinquency and a similar utilization level around 75%. The standard errors are larger for event cards, as we have a smaller number of delinquencies that satisfy the event conditions.

Focusing on Panel B, the analysis for *Net utilization*, a variable that should be equal to 1 if a card is maxed-out. We observe that this variable is in general negative for both event and non-event DO and DD cards after delinquency. Again the blue dots are higher than the red ones, but the green and orange dots are much closer to each other.

Figure 3 plots the coefficient on the interaction between *Event Month* with *Charged-off card*, for event (green dots) and non-event cards (blue dots). Thus, the blue dots show the DiD coefficient for DO vs DD cards for each event month, and the green dots are the corresponding DiD coefficient for event cards. In Panel A the dependent variable is *Net borrowing* and in Panel B *Net utilization*. In addition, we show the results for *Repayment* and *Utilization*. We observe a negative DiD coefficient for event cards (green) and a positive one for non-event cards (blue) for (net) borrowing and utilization. This indicates that, in the scenario where DO and DD cards are as similar as possible (i.e., same borrower enters delinguency in both types of cards in the same month) we find stronger evidence against strategic default. However, even for non-event cards, the DiD coefficient is well below unity, which indicates that credit available is left unutilized. Additionally, individuals tend to repay DD cards in events more than DO cards, which is the opposite of what we would expect under an opportunistic borrowing motive.

4.7 Open Questions and Additional Analysis

We answer three additional open questions that relate to the costs and benefits of opportunistic borrowing. First, how much money is left unutilized on cards that default? This amount reflects the consumption that is foregone by borrowers. Second, can borrowers predict which card they default on? We expect substantial predictability, if borrowers will opportunistically borrow on those cards. And third, are default costs unaffected by the amount the user defaulted upon? If default costs rise proportionately with the amount defaulted, then incentives to borrow opportunistically weaken.

With regards to the first question, find that roughly 0.15×4.8K=£721 could be borrowed opportunistically, on average. So a substantial amount is left on the table.

As for the second question, we run predictability regressions using card-specific information, e.g., minimum payment amounts, up until the point of delinquency to see how well we can predict which cards eventually default. Table 10 shows the result. We can predict which cards default using observables up to the time of delinquency with an R-squared of 32%. Thus, even from the observables in our dataset, predictability is substantial.

As for the final open question, we focus the analysis on the variable *Charged-off rate*, defined by the data provider as "*the probability that each account will charge off, determined by tracking accounts under the same risk band for 12 months and getting the total count of accounts that charged off as a percentage of the total observed population*". Thus, *Charged-off rate* is a measure that directly reflects a borrower's credit score and, therefore, reflects their borrowing conditions.

To illustrate how *Charged-off rate* correlates to borrowing conditions we relate it to the initial *Credit limit* and *APR* of a credit card.[5] As shown in Figure 5, the relationship is negative for *Credit limit* and positive for *APR*, showing that, on average, credit card companies, when faced with riskier borrowers, approve a lower credit limit and set a higher APR. Thus, since borrowing is more limited and more costly for individuals with a higher *Charged-off rate*, increases in *Charged-off rate* signal a deterioration of borrowing conditions. This analysis highlights that the *Charged-off rate* is a forward-looking measure that credit card companies use to adjust lending terms, making it an accurate indicator of changes in borrowing conditions following a default.

We continue to examine how the *Charged-off rate* for existing cards is affected for a given borrower when they default on their debt on a different card. We first average *Charged-off rate* for each borrower across all cards for the months before and after a charged-off event. The months after are flagged by the indicator *I(Charged-off before)*=1. For this test, we only keep borrowers who have observations both before and after a default. In Panel A of Figure

[5]This test is based on a sub-sample of cards that become active for the first time within our sample period. We only retain the first observation for these cards.

6 we plot the predicted value from a regression where the dependent variable is the average *Charged-off rate* and the regressor is *I(Charged-off before)*. When *I(Charged-off before)*=0 (before the event), the predicted *Charged-off rate* is 14%.[6] When the borrower defaults, the predicted *Charged-off rate* jumps by 13 percentage points to 27%. Thus, a default event brings significant deterioration in borrowing conditions.

In Panel B we plot the predicted value from a regression of the average *Charged-off rate* on the amount that was defaulted, conditional on *I(Charged-off before)*=1.[7] We again obtain a positive relationship but with a much smaller economic significance. For example, if a borrower defaults on £2K, the predicted *Charged-off rate* is 26.1%, and if they default on £8K, the predicted *Charged-off rate* is only 26.7%. On average, the *Credit available* in our sample is roughly £700, so this analysis suggests that the additional costs of maxing out would be relatively small compared to the overall costs of defaulting.

Figure 7 plots the dynamic responses of the charge-off rate, APRs, and credit limits of the other cards around default events (i.e., the remaining cards of a borrower, after defaulting on a separate card). We can see that defaulting on one card increases the charge-off rate, decreases APRs, and decreases credit limits. However, the interaction coefficient with amount charged off (coded in ten bins) are close to zero and appear to have the "wrong" sign for credit limits and the charge-off rate. We thus do not see the amount defaulted to be very consequential.

These findings collectively suggest that while defaulting on credit card debt substantially worsens future borrowing conditions, the magnitude of the defaulted amount does not materially exacerbate these costs. Thus, the economic incentives deterring opportunistic borrowing do not seem to be strong.

[6] For comparison, the average *Charged-off rate* in our entire sample of 1.6 million borrowers (prior to focusing on the distressed borrowers with multiple cards, etc.) is 1.5%. This is expected since the distressed borrowers in our sample are riskier.

[7] Thus, this is purely a cross-sectional regression across borrowers only for the months after a default.

4.8 What Happens After Default?

Debt collection agencies buy the debt at a fraction of the face value, often around 10%. They then harass defaulters to get their money back. However, they cannot come to homes or access defaulters' assets. Now, if personal bankruptcy is declared, a court may decide to garner defaulters' assets.[8]

However, many people who default on their credit card debt are unlikely to own any significant assets.[9] Recovery rates for credit card debt are around 25%.[10] The length of time a debt collector can chase a defaulter for a debt in the UK is governed by the Limitation Act (1980). Most unsecured debts, such as personal loans, credit cards, and utility bills, have a limitation period of six years. Once the limitation period has expired, it means the debt is statute barred and can no longer be legally enforced in court.[11] A default will stay on credit files for six years from the date of default, regardless of whether the debt is paid off. But once the default is removed, the lender wonât be able to re-register it, even if money is still owed.[12]

5 Discussion and Conclusion

Understanding the attitudes of borrowers toward strategic debt default is of crucial importance for lenders, policy-makers, and researchers. A number of studies have examined whether default is driven by considerations related to future debt payments (the long-run strategic incentive) or adverse income shocks (the short-run liquidity incentive). The results are mixed, with supportive evidence for both types of incentives.

[8] See https://moneynerd.co.uk/how-much-debt-collectors-buy-debt-for-uk/.

[9] See https://www.pewtrusts.org/en/research-and-analysis/data-visualizations/2024/who-experiences-default.

[10] See https://www.thefaircapital.com/post/the-average-collection-rate-for-a-collection-agency.

[11] See https://ukdebtexpert.co.uk/knowledge-hub/when-do-debt-collectors-give-up/.

[12] See https://www.experian.co.uk/consumer/guides/defaults.html.

In this study, we test another prediction of strategic default that has not been tested in previous work, namely whether individuals who default on their credit card debt "max-out" their credit cards before defaulting. Forward-looking and self-interested agents who know that they will default on their debt would opportunistically increase their utility if they borrowed up to the limit of their credit card just before defaulting.

We test this prediction in a setting with borrowers who become delinquent on multiple credit cards, some of which end up being charged off by the provider. The prediction by opportunistic borrowing is that the same borrower should be more willing to utilize credit on cards that are charged off relative to cards that are not. However, contrary to this prediction, we do not find any evidence of opportunistic borrowing.

Overall, our results suggest that the credit default decision is not binary, and is likely influenced by non-economic factors that temper the incentives to behave strategically, such as ethical considerations and a sense of fairness towards the credit card provider.

References

Sumit Agarwal, Chunlin Liu, and Lawrence Mielnicki. Exemption laws and consumer delinquency and bankruptcy behavior: An empirical analysis of credit card data. *Quarterly Review of Economics and Finance*, 43(2):273–289, 2003.

Leonardo Bursztyn, Stefano Fiorin, Daniel Gottlieb, and Martin Kanz. Moral incentives in credit card debt repayment: Evidence from a field experiment. *Journal of Political Economy*, 127(4):1641–1683, 2019.

Will Dobbie and Jae Song. Targeted debt relief and the origins of financial distress: Experimental evidence from distressed credit card borrowers. *American Economic Review*, 110 (4):984–1018, 2020.

Scott Fay, Erik Hurst, and Michelle J White. The household bankruptcy decision. *American Economic Review*, 92(3):706–718, 2002.

Seth M Freedman, Alex Hollingsworth, Kosali I Simon, Coady Wing, and Madeline Yozwiak. Designing difference in difference studies with staggered treatment adoption: Key concepts and practical guidelines. Technical report, National Bureau of Economic Research, 2023.

Peter Ganong and Pascal Noel. Liquidity versus wealth in household debt obligations: Evidence from housing policy in the great recession. *American Economic Review*, 110(10): 3100–3138, 2020.

Peter Ganong and Pascal Noel. Why do borrowers default on mortgages? *Quarterly Journal of Economics*, 138(2):1001–1065, 2023.

John Gathergood, Neale Mahoney, Neil Stewart, and Jörg Weber. How do individuals repay their debt? the balance-matching heuristic. *American Economic Review*, 109(3):844–75, 2019.

Kristopher Gerardi, Kyle F Herkenhoff, Lee E Ohanian, and Paul S Willen. Can't pay or won't pay? unemployment, negative equity, and strategic default. *Review of Financial Studies*, 31(3):1098–1131, 2018.

David B Gross and Nicholas S Souleles. An empirical analysis of personal bankruptcy and delinquency. *Review of Financial Studies*, 15(1):319–347, 2002.

Andrew Haughwout, Ebiere Okah, and Joseph Tracy. Second chances: Subprime mortgage modification and redefault. *Journal of Money, Credit and Banking*, 48(4):771–793, 2016.

Sasha Indarte. Moral hazard versus liquidity in household bankruptcy. *Available at SSRN 3378669*, 2020.

Christopher Mayer, Edward Morrison, Tomasz Piskorski, and Arpit Gupta. Mortgage modification and strategic behavior: Evidence from a legal settlement with countrywide. *American Economic Review*, 104(9):2830–2857, 2014.

Therese C Scharlemann and Stephen H Shore. The effect of negative equity on mortgage default: Evidence from hamp's principal reduction alternative. *Review of Financial Studies*, 29(10):2850–2883, 2016.

Table 1: Summary Statistics

	Mean	Standard deviation	Median	5th percentile	25th percentile	75th percentile	95th percentile
Discretionary spending	96.61	331.0	0	0	0	9.500	577.3
Charges and fees	49.90	64.44	26.83	0	0	71.96	190.7
Repayment	108.7	256.5	39.56	0	0	105	380
Net borrowing	-10.88	339.8	-18.81	-300	-81.57	0	391.1
Revolving balance	3425.9	3406.6	2485.3	0	814.9	4855.6	10676.0
Credit available	1231.3	2181.4	241.5	0	0	1359.7	6200.0
Utilization	0.747	0.350	0.915	0	0.580	0.990	1.080
Net utilization	-0.254	1.308	-0.0122	-1.379	-0.105	0	0.762
Credit limit	4807.7	3868.8	3800	500	1950	6575	13250
APR	0.223	0.0568	0.219	0.158	0.170	0.264	0.299
Observations per customer	59.45	22.38	51	40	50	70	101
Number of customers per month-by-year	3535.3	2040.9	3536	343	1771	5309	6707
Observations (total)	330,210						

Table 2: Net Borrowing and Credit Available

	(1) Max-out hypothetical net borrowing	(2) Actual net borrowing
Credit available	0.055***	0.055***
	(0.002)	(0.002)
Charged-off card =1 × Credit available	0.012***	0.012***
	(0.003)	(0.003)
0-6 months after delinquency =1 × Credit available	-0.038***	-0.038***
	(0.002)	(0.002)
0-6 months after delinquency =1 × Charged-off card =1 × Credit available	0.971***	-0.017***
	(0.003)	(0.003)
Individual × month-by-year fixed effects	✓	✓
Observations	287,454	287,368
Adjusted R^2	0.466	0.144
Sum of the test coefficients (max-out hypothesis: $sum = 1$)	1.000	0.012
Max-out hypothesis: p-value	0.798	0.000

This table presents our baseline results. We retain in our sample individuals who go delinquent on more than one card during the sample period. We classify an individual as entering delinquency in a card in month t if the variable cycles delinquent (CD), which counts the number of months that the individual has failed to make the minimum payment as of that month, is $CD_{t-1} = 0$ and $CD_t > 0$ and $CD_{t+1} > 0$. *Credit available* is calculated as the credit limit of the card at the end of each month month t minus the amount of fees paid during month t (e.g., interest charges, penalties, etc) minus the balance of the card at the beginning of month t. If *Credit available* is negative we set it to zero. *Net Borrowing* is the difference between borrowing in month t and repayments in month t. The indicator *Charged-off card* is set to 1 if a card that enters delinquency is eventually charged-off. *1-3 months before delinquency* is an indicator that equals 1 for the months from $t-3$ to $t-1$. *0-6 months after delinquency* is an indicator that equals 1 for the months from t to $t+6$. *More than 6 months after delinquency* is an indicator that equals 1 for the months from $t+7$ onwards. In Column (1) we calculate *Net borrowing* in a hypothetical scenario where the individual maxed-out the card that entered delinquency in month $t = 0$ that was eventually charged-off (i.e., borrowed up to the credit limit on that card in month $t+1$). In Column (2) we estimate the same model using the actual *Net borrowing* variable. The last two rows present the coefficient and p-value on *Credit available* when *Post delinquency* and *Charged-off card* are equal to 1. Standard errors are clustered at the individual and year-month levels with p-values indicated by * <0.1; ** <0.05; *** <0.01.

Table 3: Net Borrowing and Credit Available: Cross-Sectional Heterogeneity

	(1) Net borrowing	(2) Net borrowing	(3) Net borrowing	(4) Net borrowing	(5) Net borrowing	(6) Net borrowing
Credit available	0.050***	0.052***	0.046***	0.072***	0.055***	0.051***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Charged-off =1 × Credit available	0.012***	0.011**	0.009***	0.012**	0.012***	0.018***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)
0-6 months after delinquency =1 × Charged-off =1 × Credit available	-0.021***	-0.014***	-0.002	-0.016**	-0.017***	-0.022***
	(0.004)	(0.005)	(0.005)	(0.007)	(0.003)	(0.005)
Charged-off =1 × Group interaction =1 × Credit available	-0.045**	0.001	0.007	0.003	-0.135	-0.015**
	(0.018)	(0.007)	(0.008)	(0.006)	(0.087)	(0.007)
0-6 months after delinquency =1 × Charged-off=1 × Group interaction =1 × Credit available	-0.008	-0.004	-0.026**	-0.004	0.134	0.014*
	(0.049)	(0.007)	(0.010)	(0.008)	(0.087)	(0.007)
Group interaction	Above median utilization	Above median revolving balance	Above median minimum payment	Above median holding time	Charged-off before	Above median N cards
Individual × month-by-year fixed effects	✓	✓	✓	✓	✓	✓
Observations	287,368	287,368	287,368	287,368	287,368	287,368
Adjusted R^2	0.294	0.148	0.152	0.150	0.144	0.145

This table examines for cross-sectional heterogeneity according to the definition of the indicator *I(Group)*, which takes the value of 1 if a specific variable for card i in month t is above the sample median. In Column (1) the variable is utilization, in Column (2) revolving balance, in Column (3) minimum payment, in Column (4) the holding time of the specific credit card (since the card was first obtained). In Column (5) *I(Group)* takes the value of 1 if the specific borrower has experienced a charge-off before for another card. In Column (6) *I(Group)* takes the value of 1 if the specific borrower has an above median number of credit cards. Variable definitions and sample construction criteria are as in Table 2. Standard errors are clustered at the individual and year-month levels with p values indicated by $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 4: Net Borrowing and Credit Available: Quantile Regressions

	(1) Net borrowing	(2) Net borrowing	(3) Net borrowing	(4) Net borrowing	(5) Net borrowing
Credit available	0.045***	0.047***	0.059***	0.064***	0.066***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Charged-off × Credit available	0.007**	0.008**	0.014***	0.017***	0.018***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
0-6 months after delinquency × Credit available	-0.031***	-0.032***	-0.041***	-0.045***	-0.047***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
0-6 months after delinquency × Charged-off × Credit available	-0.012***	-0.013***	-0.018***	-0.021***	-0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Quantile	0.1	0.3	0.5	0.7	0.9
Individual × month-by-year fixed effects	✓	✓	✓	✓	✓
Observations	312,646	312,646	312,646	312,646	312,646

This table estimates our baseline model from Table 2 using quantile regressions, where we estimate specific quantiles of the conditional distribution of *Net Borrowing*. The exact quantile that is being estimated is shown at the top of each column. Standard errors are clustered at the individual level with p values indicated by $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

Table 5: Net Borrowing and Credit Available: Clean Controls

	(1) Max-out hypothetical net borrowing	(2) Actual net borrowing
Credit available	0.054***	0.054***
	(0.002)	(0.002)
0-6 months after delinquency =1 × Credit available	-0.036***	-0.036***
	(0.002)	(0.002)
Charged-off card =1 × Credit available	0.012***	0.012***
	(0.004)	(0.004)
0-6 months after delinquency =1 × Charged-off card =1 × Credit available	0.974***	-0.016***
	(0.004)	(0.004)
Individual × month-by-year fixed effects	✓	✓
Observations	6,177,030	6,169,418
Adjusted R^2	0.718	0.559
Sum of the test coefficients (max-out hypothesis: $sum = 1$)	1.003	0.013
Max-out hypothesis: p-value	0.160	0.000

This table presents the same analysis as Table 2 when we use a clean-control estimating procedure where we create one stack for each treatment ($Charged-off card$) using only clean controls, i.e., individuals that were not charged-off at all over the sample period. Variable definitions and sample construction criteria are as in Table 2. In Column (1) we calculate *Net borrowing* in a hypothetical scenario where the individual maxed-out the card that entered delinquency in month $t = 0$ and was eventually charged-off (i.e., borrowed up to the credit limit on that card in month $t + 1$). In Column (2) we estimate the same model using the actual *Net borrowing* data. The row H_0: Max-out presents the $p-$value from a test that examines if the coefficient on *Credit available* is 1 when *Charged-off card* and *0-6 months after delinquency* equal 1. Standard errors are clustered at the individual and year-month levels with p values indicated by $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 6: Covariance Balance Test

	All delinquent cards			Cards part of delinquencies with $N > 1$ cards and $N > n > 1$ charged off				
	Observations	Mean	Standard error	Observations	Mean	Standard error	Difference	P-value
Discretionary spending	296,173	96.19	0.61	34,037	100.28	1.85	-4.09	0.65
Charges and fees	296,173	50.35	0.12	34,037	45.94	0.34	4.41	0.00
Repayment	296,173	109.64	0.47	34,037	100.11	1.31	9.53	0.00
Net borrowing	296,173	-12.13	0.63	34,037	-0.00	1.81	-12.13	0.00
Revolving balance	280,427	3369.30	6.41	32,291	3917.02	19.25	-547.72	0.00
Credit available	280,355	1247.47	4.17	32,291	1091.19	10.66	156.28	0.00
Utilization	280,355	0.74	0.00	32,291	0.80	0.00	-0.05	0.00
Net utilization	284,523	-0.26	0.00	32,664	-0.22	0.01	-0.04	0.00
Credit limit	296,098	4771.37	7.12	34,037	5124.10	20.61	-352.73	0.00
APR	291,583	0.22	0.00	33,539	0.22	0.00	0.01	0.00

This table presents a covariance balance test, comparing various credit card variables between borrowers who go delinquent on multiple cards simultaneously and delinquent borrowers in our overall sample, who can go delinquent on different cards in different months.

Table 7: Net Borrowing and Credit Available: Aligning Delinquency Time

	(1) Max-out hypothetical net borrowing	(2) Actual net borrowing
Credit available	0.054***	0.054***
	(0.002)	(0.002)
0-6 months after delinquency =1 × Credit available	-0.037***	-0.037***
	(0.002)	(0.002)
Charged-off card =1 × Credit available	0.013***	0.013***
	(0.004)	(0.004)
0-6 months after delinquency =1 × Charged-off card =1 × Credit available	0.974***	-0.016***
	(0.004)	(0.004)
Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1 × Credit available	0.019***	0.019***
	(0.006)	(0.006)
0-6 months after delinquency =1 × Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1 × Credit available	-0.024***	-0.026***
	(0.007)	(0.007)
Charged-off card =1 × Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1 × Credit available	-0.012	-0.012
	(0.009)	(0.009)
0-6 months after delinquency =1 × Charged-off card =1 × Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1 × Credit available	0.001	0.013
	(0.011)	(0.011)
Individual × month-by-year fixed effects	✓	✓
Observations	287,454	287,368
Adjusted R^2	0.466	0.144
Sum of the test coefficients (max-out hypothesis: *sum* = 1)	1.004	0.013
Max-out hypothesis: p-value	0.123	0.000

This table presents a test that aligns the start of delinquency for DD and DO cards. We retain in our sample individuals who hold more than one credit card, and who go delinquent on at least one card during the sample period. We classify an individual as entering delinquency in a card in month t if the variable cycles delinquent (CD), which counts the number of months that the individual has failed to make the minimum payment as of that month, is $CD_{t-1} = 0$ and $CD_t > 0$ and $CD_{t+1} > 0$. *Credit available* is calculated as the credit limit of the card at the end of each month month t minus the amount of fees paid during month t (e.g., interest charges, penalties, etc) minus the balance of the card at the beginning of month t. If *Credit available* is negative we set it to zero. *Net Borrowing* is the difference between borrowing in month t and repayments in month t. The indicator *Charged-off card* is set to 1 if a card that enters delinquency is eventually charged-off. We set the indicator *Delinquencies of* $N > 1$ *cards and* $N > n > 1$ *charged off* equal to 1 when a borrower who never experienced default before goes delinquent in $N_D > 1$ cards in month $t = 0$ and has $N_C < N_D$ of these cards ultimately charged off. *1-3 months before delinquency* is an indicator that equals 1 for the months from $t-3$ to $t-1$. *0-6 months after delinquency* is an indicator that equals 1 for the months from t to $t+6$. *More than 6 months after delinquency* is an indicator that equals 1 for the months from $t+7$ onwards. In Column (1) we calculate *Net borrowing* in a hypothetical scenario where the individual maxed-out the card that entered delinquency in month $t = 0$ that was eventually charged-off (i.e., borrowed up to the credit limit on that card in month $t+1$). In Column (2) we estimate the same model using the actual *Net borrowing* variable. The last two rows present the coefficient and p-value on *Credit available* when *0-6 months after delinquency* and *Charged-off card* are equal to 1. Standard errors are clustered at the individual and year-month levels with p-values indicated by * <0.1; ** <0.05; *** <0.01.

Table 8: Credit Card Outcomes around Delinquency

	(1) Discretionary spending	(2) Charges and fees	(3) Repayment	(4) Net borrowing	(5) Revolving balance	(6) Utilization	(7) Net utilization	(8) Credit limit	(9) APR
0-6 months after delinquency =1	-53.196***	11.945***	-30.423***	-19.118***	421.241***	0.032***	0.074***	107.149	-0.001
	(4.986)	(1.766)	(4.157)	(4.444)	(88.994)	(0.009)	(0.026)	(110.583)	(0.002)
0-6 months after delinquency =1 × Charged-off =1	-5.526	-3.898**	-28.221***	20.264***	508.167***	0.028***	0.128***	375.471***	0.002
	(6.764)	(1.758)	(4.543)	(4.865)	(106.348)	(0.009)	(0.025)	(127.755)	(0.002)
More than 6 months after delinquency =1	-52.961***	1.429	-29.557***	-21.499***	166.101	-0.079***	0.095***	109.122	-0.001
	(6.795)	(2.512)	(5.128)	(5.188)	(136.540)	(0.015)	(0.029)	(174.839)	(0.003)
More than 6 months after delinquency =1 × Charged-off=1	-4.386	-20.026***	-24.437***	17.024***	988.127***	0.133***	0.085***	479.160**	-0.006*
	(7.641)	(2.878)	(5.169)	(5.388)	(182.770)	(0.017)	(0.028)	(195.292)	(0.003)
Individual × month-by-year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	301,526	301,526	301,526	301,526	287,496	287,368	289,165	301,392	294,580
Adjusted R^2	0.159	0.444	0.247	0.087	0.430	0.523	0.081	0.404	0.288

This table presents credit card outcomes around delinquency events. Variable definitions and sample construction criteria are as in Table 2. In all regressions, we control for the interaction of individual and month-by-year fixed effects. Standard errors are clustered at the individual and year-month levels with p values indicated by $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

Table 9: Credit Card Outcomes around Delinquency

	(1) Discretionary spending	(2) Charges and fees	(3) Repayment	(4) Net borrowing	(5) Revolving balance	(6) Utilization	(7) Net utilization	(8) Credit limit	(9) APR
0-6 months after delinquency =1	-54.387***	10.802***	-29.349***	-21.841***	358.259***	0.025**	0.058**	48.174	-0.000
	(5.043)	(1.742)	(4.433)	(4.365)	(92.481)	(0.010)	(0.026)	(114.918)	(0.002)
0-6 months after delinquency =1 × Charged-off =1	-0.686	0.751	-31.436***	30.580***	729.793***	0.049***	0.181***	592.278***	0.001
	(7.986)	(2.432)	(5.274)	(6.225)	(136.735)	(0.012)	(0.033)	(163.348)	(0.002)
0-6 months after delinquency =1 × Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1	2.040	3.572	-9.105	13.387	231.630	0.015	0.114*	179.170	0.003
	(16.914)	(3.469)	(10.248)	(14.698)	(199.598)	(0.021)	(0.059)	(155.840)	(0.003)
0-6 months after delinquency =1 × Charged-off =1 × Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1	-13.669	-13.727***	9.536	-29.962***	-628.214***	-0.060***	-0.156***	-609.441***	0.002
	(12.611)	(3.770)	(9.357)	(8.223)	(165.153)	(0.017)	(0.044)	(176.096)	(0.003)
More than 6 months after delinquency =1	-54.017***	0.855	-28.780***	-23.522***	115.069	-0.085***	0.083***	54.896	-0.000
	(6.959)	(2.530)	(5.335)	(5.161)	(139.540)	(0.015)	(0.028)	(179.305)	(0.003)
More than 6 months after delinquency =1 × Charged-off =1	0.208	-17.375***	-26.647***	25.039***	1275.218***	0.163***	0.123***	758.541***	-0.007*
	(9.269)	(3.597)	(5.936)	(7.070)	(213.274)	(0.020)	(0.035)	(231.886)	(0.004)
More than 6 months after delinquency =1 × Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1	0.019	-1.305	-10.571	12.139	-298.784	-0.003	0.172**	-94.172	0.005
	(17.526)	(5.264)	(12.243)	(14.211)	(374.858)	(0.031)	(0.064)	(405.205)	(0.006)
More than 6 months after delinquency =1 × Charged-off =1 × Delinquencies of $N > 1$ cards and $N > n > 1$ charged off =1	-13.081	-5.953	7.133	-21.953*	-1060.425***	-0.117***	-0.109*	-959.467**	0.006
	(13.532)	(6.147)	(11.206)	(11.201)	(375.298)	(0.028)	(0.056)	(402.882)	(0.007)
Individual × month-by-year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	301,526	301,526	301,526	301,526	287,496	287,368	289,165	301,392	294,580
Adjusted R^2	0.159	0.444	0.247	0.087	0.430	0.524	0.081	0.405	0.289

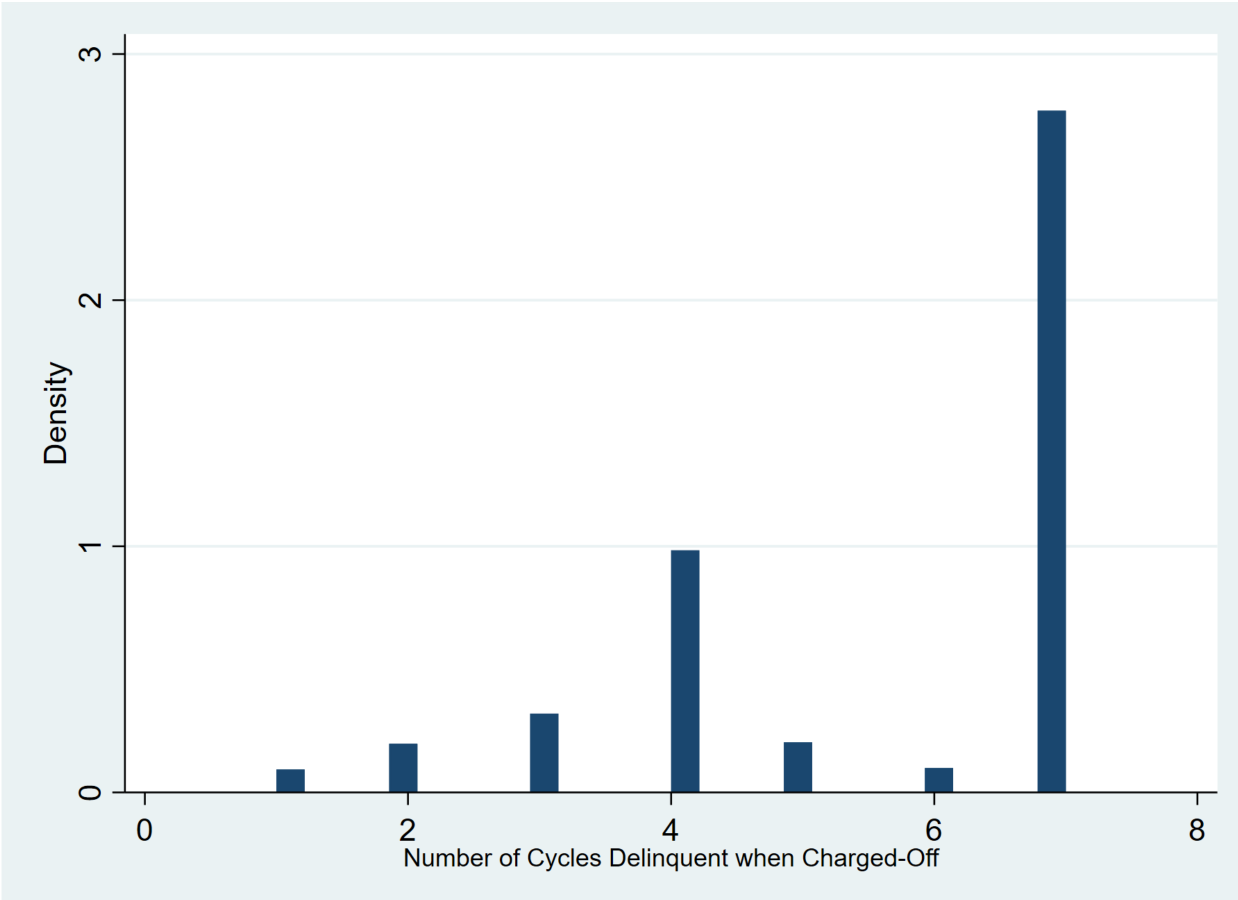
This table presents credit card outcomes around delinquency events. Variable definitions and sample construction criteria are as in Table 2. In all regressions, we control for the interaction of individual and month-by-year fixed effects. Standard errors are clustered at the individual and year-month levels with p values indicated by $^{*}p$<0.1; $^{**}p$<0.05; $^{***}p$<0.01.

Table 10: Is Default Predictable?

	(1) Charged-off	(2) Charged-off	(3) Charged-off	(4) Charged-off
Minimum payment		0.000***	-0.000***	
		(0.000)	(0.000)	
APR		3.972***	3.829***	
		(0.092)	(0.091)	
Credit available			0.000***	
			(0.000)	
Utilization			0.040**	
			(0.018)	
Revolving balance			0.000***	
			(0.000)	
Mismatched due date			-0.089***	
			(0.008)	
Card age			-0.000**	
			(0.000)	
All continuous variables in 10 bins				✓
Individual fixed effects	✓	✓	✓	✓
Observations	21,008	19,496	19,496	19,496
R^2	0.070	0.167	0.220	0.311

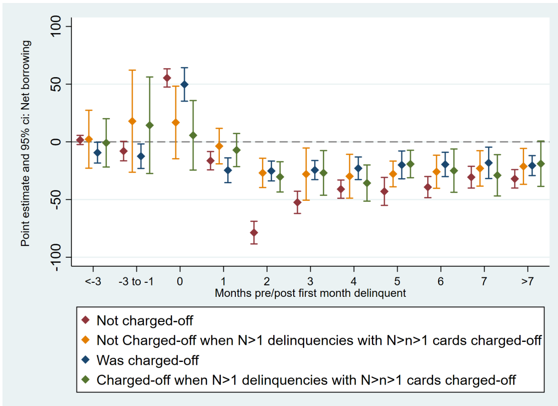
This table presents the results of predicting which card will default using different sets of card-specific variables.

Figure 1: Months Delinquent at Charge-Off

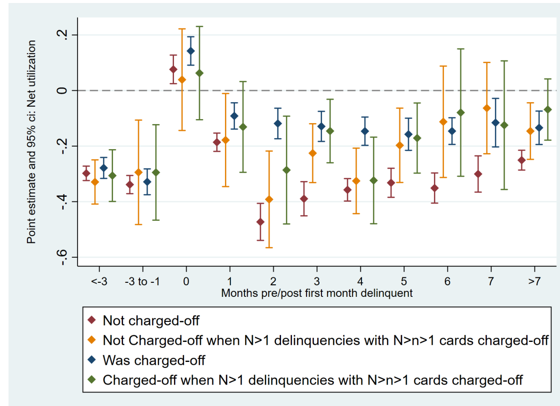


These figure shows the number of months a card is delinquent before being charged off by the credit card provider.

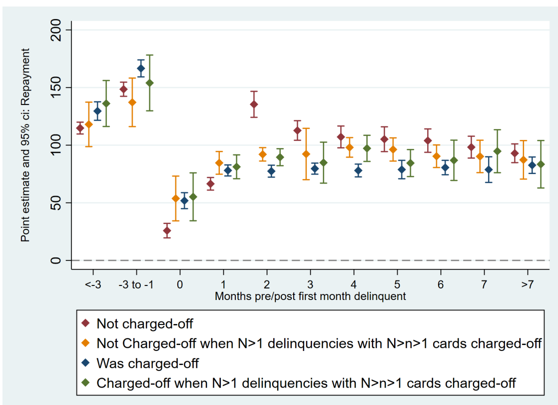
Figure 2: Margin plots Utilization and Net Utilization around Delinquency



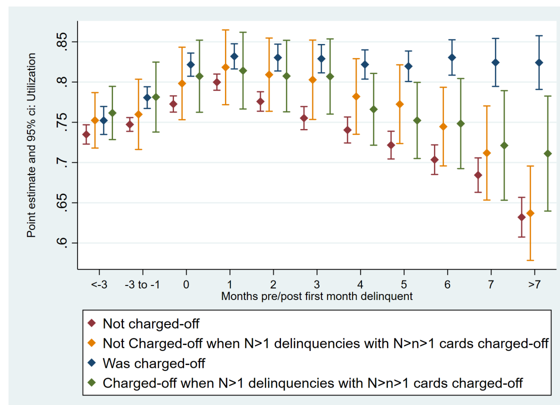
(A): Net borrowing



(B): Net utilization



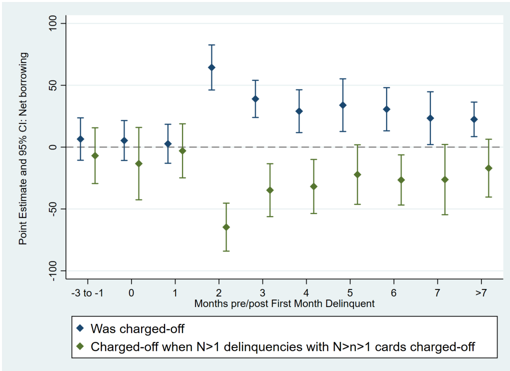
(D): Repayment



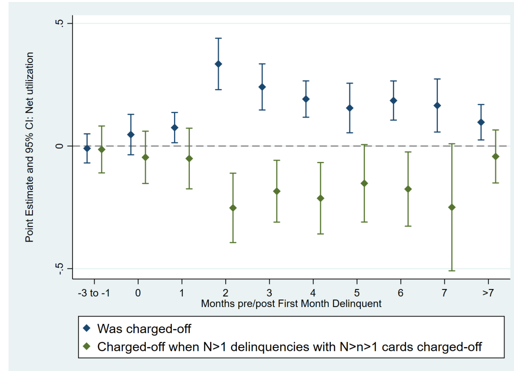
(D): Utilization

These figures show margin plots of the coefficients on the months around delinquencies for cards that are ultimately charged off versus not. In Panel (A) the dependent variable is *Net borrowing*, in (B) it is *Net utilization*, in (C) it is *Repayment*, and in (D) it is *Utilization*. In all regressions, we control for the interaction of individual and month-by-year fixed effects. The displayed standard error bars are obtained by clustering at the individual and month-by-year levels.

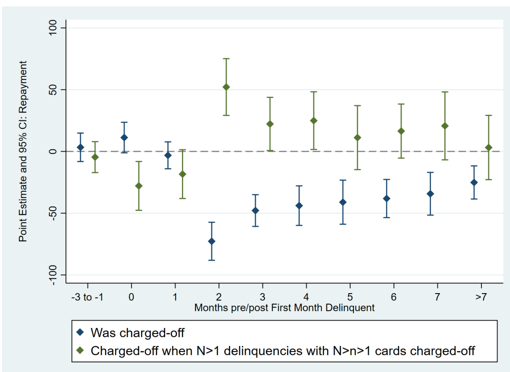
Figure 3: Dynamic Analysis of Credit Card Outcomes around Delinquency



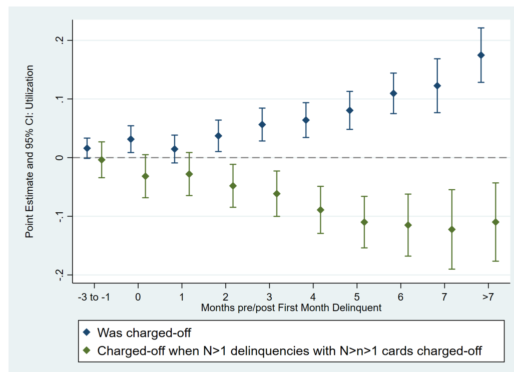
(A): Net borrowing



(B): Net utilization



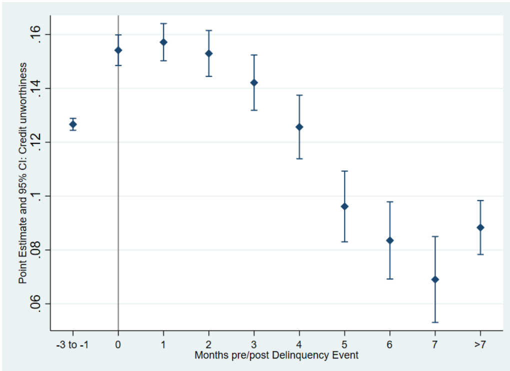
(D): Repayment



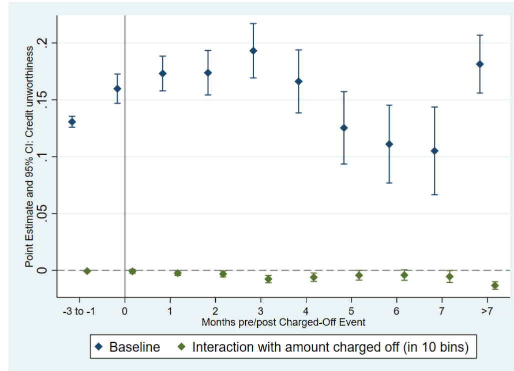
(D): Utilization

These figures show the coefficients on the interaction of the months around delinquencies with a dummy that flags whether a card has been ultimately charged off. In Panel (A) the dependent variable is *Net borrowing*, in (B) it is *Net utilization*, in (C) it is *Repayment*, and in (D) it is *Utilization*. In all regressions, we control for the interaction of individual and month-by-year fixed effects. The displayed standard error bars are obtained by clustering at the individual and month-by-year levels.

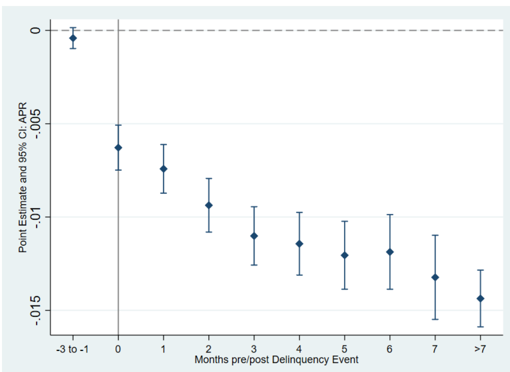
Figure 4: Dynamic Analysis of Credit Scores, APRs, and Limits around Charge-Off



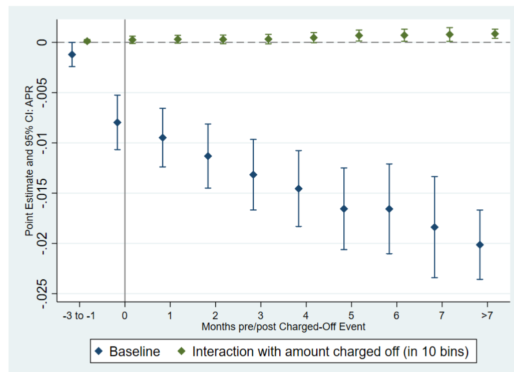
(A): Charge-off rate



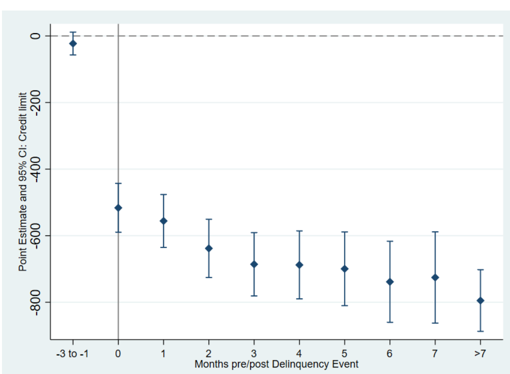
(B): Charge-off rate



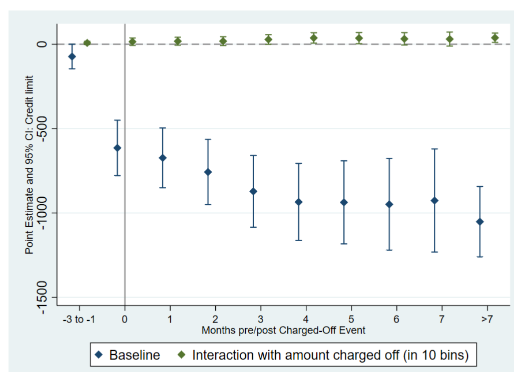
(C): APRs



(D): APRs



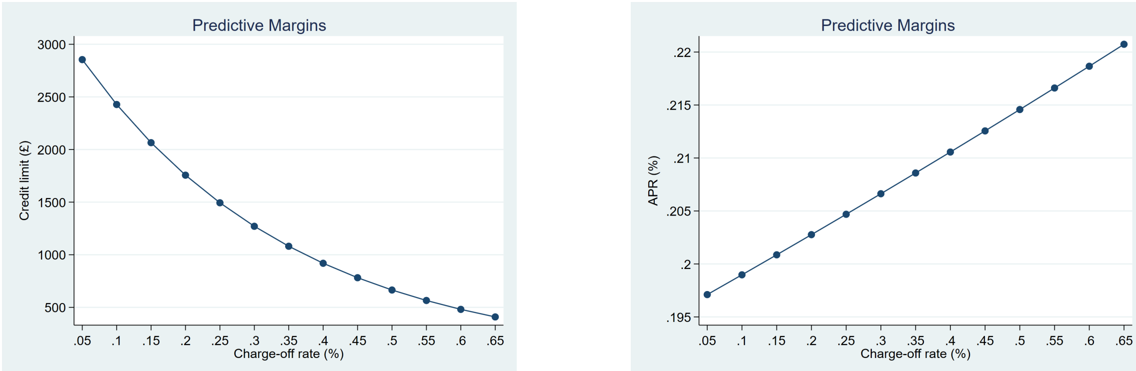
(D): Credit limits



(F): Credit limits

On the left side, these figures show the coefficients on the *Charged-off rate*, *APR*, and *Credit limit* of all borrowers' cards when one gets charged off. On the right side, the figures shows the baseline coefficients as well as the interaction coefficients with the amount charged off. In Panels (A) and (B) the dependent variable is *Charge-off rate*, in (C) and (D) it is *APR*, and in (E) and (F) it is *Credti limit*. The variable *Amount charged-off* is coded in 10 bins of amount charged off on the card that defaults. In all regressions, we control for individual and month-by-year fixed effects. The displayed standard error bars are obtained by clustering at the individual and month-by-year levels.

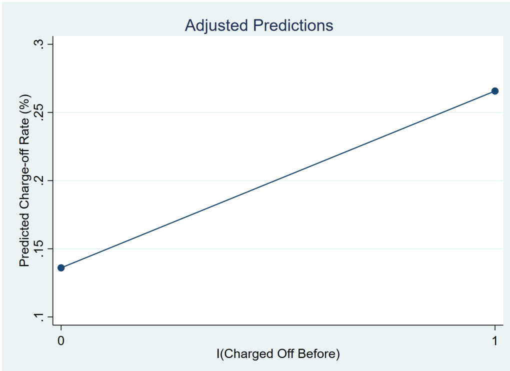
Figure 5: Charged-off rate, Credit Limit and APR



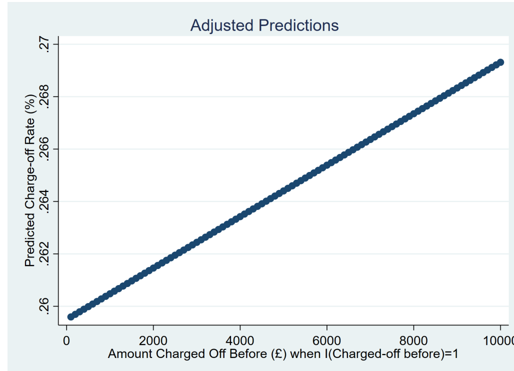
(A): Credit Limit (B): APR

These figures shows the predicted value from a generalized linear model where the dependent variable is *Credit limit* (Panel A) and APR (Panel B). The independent variable is *Charge-off rate*, defined (by the data provider) as "the probability that each account will charge off. This is determined by tracking accounts under the same risk band for 12 months and getting the total count of accounts that charged off as a percentage of the total observed population then applying that percentage rate as the unit charge off rate of the given account." We use a logit link function and assume a Gaussian distribution for the dependent variable. We use in the model only cases where the first observation (row) for a credit card in our sample is the date that the card was opened. We use month-by-year fixed effects in the model, and cluster the standard errors by month by year.

Figure 6: Charged-Off Rate, Default and Default Amount



(A): Charged-off rate before and after default

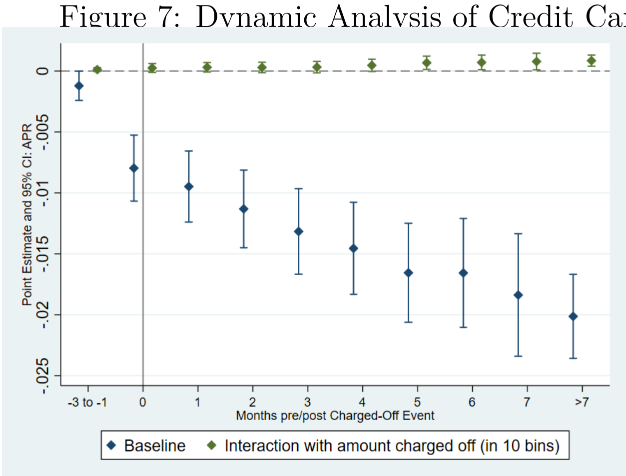


(B): Charged-off rate and amount defaulted

These figures shows the predicted value from a regression model where the dependent variable is *Charged-off rate*. We first average *Charged-off rate* for each borrower across all cards for the months before and after a charge-off event. The months after are flagged by the indicator *I(Charged-off before)*=1. We only keep borrowers in the sample who have observations both before and after a default. If the *Charged-off rate* is missing for a specific card in month t we set it equal to its last non- missing value for that card. In Panel A we regress the average *Charged-off rate* on *I(Charged-off before)*. In Panel B we regress the average *Charged-off rate* on the amount that was defaulted, conditional on *I(Charged-off before)*=1.

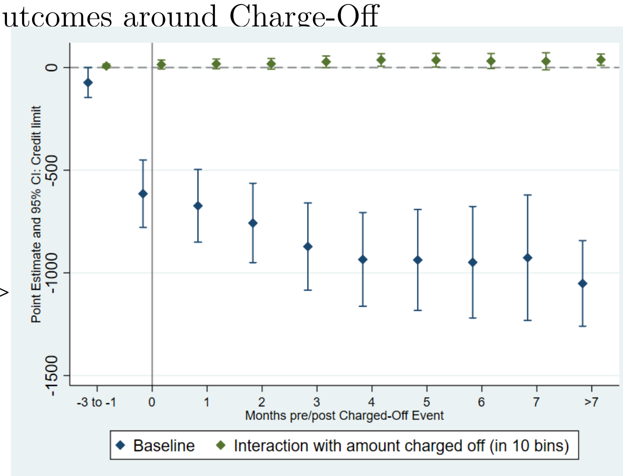
Figure 7: Dynamic Analysis of Credit Card Outcomes around Charge-Off

<1>



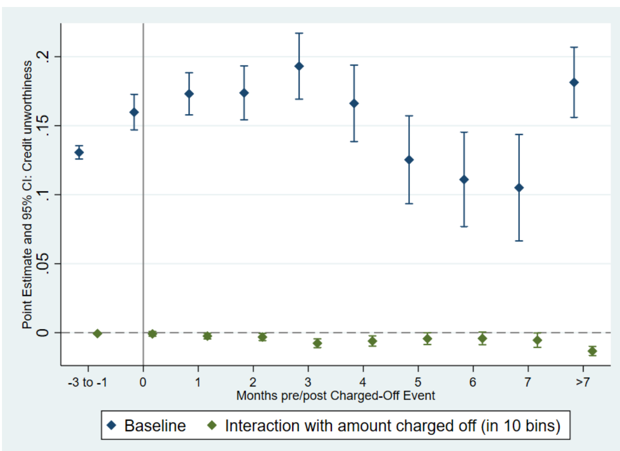
(A): APRs

<2>



(B): Credit limits

<3>



(C): Credit Unworthiness