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

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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 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 users borrow less and repay more on the delinquent cards that are ultimately charged off. We then use a structural model to quantify two explanations for the lack of opportunistic borrowing in the credit card market: first, sensitivity of default penalties to the borrowed amount (which are not present in the data), and second, mistaken beliefs about the likelihood of cards being charged off after delinquencies.

Keywords: Credit card delinquencies, credit card borrowing, strategic default, structural modeling

JEL Codes: G5, D14

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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 the debt was charged off. For historical comparison, the delinquency rate peaked in the second quarter of 2009 at 6.77% and 10.54% of that debt was charged off.[1] A key question – with important and far-reaching implications for credit risk modeling, pricing, and regulatory policy – is whether borrowers default out of necessity or as a strategic economic decision.

A few previous studies find that strategic motives influence credit-card default. Fay et al. [2002] use surveys to show that households default more when the debt to be written off is larger. In cross-sectional studies, Agarwal et al. [2003] and Gross and Souleles [2002] document higher default rates where exemption laws are more generous or when social stigma is reduced. Dobbie and Song [2020] provide causal evidence from exogenous offers of delayed interest write-downs and find that default rates fall immediately – well before the write-downs take effect – indicating that borrowers' expectations of future relief temper their incentive to default strategically. We build on this literature by examining a new and previously unexplored form of strategic behavior: *opportunistic borrowing* on credit cards that are eventually written off.

Opportunistic borrowing occurs when borrowers, anticipating that they may default on a given card, strategically borrow the card's remaining credit to benefit financially before defaulting. This behavior enables borrowers to increase current consumption while shifting the losses onto credit-card issuers. Even though the credit-card industry is concerned about such borrowing,[2] no academic study has examined its prevalence. Indeed, if such borrowing

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

[2] See Investopedia, "Bust-Out Credit Card Fraud: Definition and Impact" (accessed 30 June 2025); and Liberty Street Economics, "Delinquency Is Increasingly in the Cards for Maxed-Out Borrowers," 3 Feb 2025.

is widespread, it would add an important new dimension to strategic defaults, beyond the commonly studied choice of continuing or stopping repayments. Using a structural model as well as a rich panel of consumer-level credit-card data, we study the dynamics of borrowing around delinquency and default to provide the first evidence on opportunistic borrowing.

We start our analysis by using a discrete-choice model to analyze the borrowing decisions of a forward-looking agent facing delinquency and default. The purpose of this exercise is twofold. First, we show that opportunistic borrowing before default is a robust feature of agents' optimal utilization policies. Second, we illustrate how agents' propensity to opportunistically borrow in anticipation of default varies with key model parameters: the costs of default, the sensitivity of default penalties to the borrowed amount, and the probability of default conditional on delinquency.

We then use a dataset covering more than 1.6 million credit card borrowers over a period of 2 years in the UK [see also 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. We can thus analyze a large number of these rare events.

The main challenge in isolating strategic motives in credit-card default is that time-varying, borrower-specific forces like income and liquidity shocks, or evolving expectations about default costs, jointly shape both delinquency and borrowing. Cross-sectional comparisons of cards that become delinquent and later default (DD cards) versus those that become delinquent only but eventually cure (DO cards) are therefore confounded by unobserved differences across borrowers. Crucially, even within the same borrower across time, DD-DO comparisons are not clean: the relevant shocks, beliefs, and contractual terms change from month to month, and the borrower may re-optimize which card to use or protect as circumstances evolve. As a result, longitudinal within-borrower contrasts still mix strategic behavior with changing conditions at the borrower-month level.

To address this identification challenge, we focus on situations when borrowers default on multiple cards simultaneously (in the same billing cycle) and eventually default on some of them. Because the delinquency-onset month is identical for DD and DO cards, the income or liquidity shocks that trigger delinquency are common to both types of cards in that borrower-month. We can thus control for borrower-by-month fixed effects, which difference out the shared shocks, leaving only within-borrower, within-month variation in borrowing behavior across DD and DO cards, thus allowing us to cleanly test for opportunistic borrowing.

The dependent variable in our model is *Net Borrowing*, defined as $NetBorrowing_{j,t} = Spending_{j,t} - Repayment_{j,t}$ measured on card j in month t. The key independent variables are: *Post (0,6)*, which equals 1 in the six months after card j enters delinquency; *Charged-off*, which equals 1 if card j is a DD card that is eventually charged off; and *Delinq Aligned*, which equals 1 if the borrower entered delinquency on card j in the same month as on her other cards. Our DD–DO comparisons focus on the aligned cases, so that the delinquency shock is common across card types.

The main regressor of interest is *Credit available* on card j. Its coefficient captures the sensitivity of net borrowing to available credit. We estimate the model by interacting all the independent variables, and then use the estimated coefficients to recover the sensitivity of net borrowing to credit availability for DD versus DO cards in post-delinquency periods when *Delinq Aligned* $= 1$, i.e., during the post-delinquency span after multiple cards went delinquent and some but not all of them were charged off.

We test two versions of the opportunistic borrowing hypothesis. The *strong test* is that the coefficient on *Credit available* is equal to 1 for the interaction of all three indicators ($Post(0,6), Charged\text{-}off,$ and *Delinq Aligned*), consistent with maxing-out behavior—i.e., a one-to-one relationship between net borrowing and credit availability when the card is eventually charged-off.

The *weak test* is that the difference in coefficients between DD and DO cards, conditional on $Post(0,6)$ and $DelinqAligned$ being equal to 1, is positive, indicating a stronger propensity to draw down available credit on DD cards.

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 the cases where *Delinq Aligned* $= 1$. In contrast, no credit is borrowed on DO cards. In this "maxing-out" scenario, the coefficient on credit available under the strong opportunistic borrowing hypothesis is, as expected, statistically indistinguishable from 1. Under the weak-opportunistic borrowing, the difference in slopes between DD and DO cards is also positive (equal to 1).

We find no evidence of opportunistic borrowing in the actual data. In stark contrast to the counterfactual scenario, the estimated coefficient on *Credit available* for charged-off cards post delinquency is only 0.007, which strongly rejects the one-to-one relationship between borrowing and credit availability predicted by the strong test of opportunistic borrowing. Similarly, under the weak test, the difference in slopes between DD and DO cards is -0.003, comfortably failing to reject the null of no difference.

We also analyze the dynamic patterns of net borrowing, repayment, utilization and net utilization (defined as $Net\ Borrowing/CreditAvailable$) around delinquency for DO and DD cards. We find that net borrowing and net utilization are negative for both types of cards after delinquency. Repayment drops relative to pre-delinquency months, but remains positive, which means that borrowers continue to make payments after delinquency. Utilization rises slightly after delinquency, but then drops and levels off at about 75% on average, indicating that a significant amount of credit is left unused for DD cards.

Taken together, our evidence rules out opportunistic borrowing. In aligned episodes, DD and DO cards exhibit statistically indistinguishable post-delinquency behavior in the sensitivity

of net borrowing to credit available, consistent with mistaken beliefs about default costs or default probabilities, or with non-pecuniary motives (e.g., social stigma, fairness) that deter maxing out. Moreover, we document a broad reduction in net borrowing across cards once delinquency begins. To our knowledge, this is the first evidence of such reductions, even when credit lines remain available–contrary to canonical consumption-smoothing models that imply borrowing should rise to smooth consumption after a negative income shock.

We then explore heterogeneity in strategic borrowing by examining whether 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 an increase in opportunistic borrowing. 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, even the latter group of individuals does not borrow opportunistically but merely keep their net borrowing unchanged on DO cards versus DD cards.

The previous empirical setting 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 (and 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 indicates that DD cards that are part of a multi-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*.[3] 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 is not supported by the data. Beyond the *Charged-off rate*, we also show that APRs and

[3]This variable is the credit card provider determined probability that a borrower in that particular risk band will default.

credit limits on other cards are not affected by the amount defaulted.

Why do we not observe opportunistic borrowing? To answer this question we use our structural model to examine which factors temper borrowers' incentive to draw down credit for DD cards, focusing on three specific factors: the fixed cost of default, the sensitivity of default penalties to the borrowed amount, and the probability of default conditional on delinquency. Sensibly, high fixed default costs deter borrowing in the first place and reduce the probability of delinquency and default. However, conditional on delinquency, fixed default costs do not deter opportunistic borrowing because the borrower will pay these costs anyway, regardless of the defaulted amount.

Higher sensitivity of default costs to the outstanding balance strongly discourages opportunistic borrowing near delinquency. In this case, the marginal cost of borrowing in the face of default risk increases, prompting borrowers to limit their credit use to avoid larger penalties later on. This discourages opportunistic borrowing as default becomes more costly. However, our empirical evidence showing that, conditional on a default on another card, the borrowing costs do not rise with the amount defaulted, indicate that this channel is unlikely to be driving our results.

Finally we analyze the effect of default risk, i.e., the probability perceived by the borrower on their card being eventually charged off. The model shows that, when default is highly likely after delinquency, borrowers are more inclined to max-out their cards defaulting. Expectations about default thus play a key role in shaping strategic borrowing behavior. Individuals must be mistaken about the probability of default after they went delinquent and seem to be delusional about keeping the doomed cards alive.

The next section reviews the relevant literature and highlights our contribution. Section 2 presents the discrete choice model of borrowing and delinquency to illustrate 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

In this section, we analyze the credit utilization of a forward-looking agent facing both income and default risk. The aim of this section is to first verify that opportunistic borrowing in advance of default is to be expected among rational agents. We also discuss in detail how two model features affect opportunistic borrowing: specifically, the costs of defaulting and what determines which and when a card is charged off.

Consider a single agent with an infinite time horizon. In each period t, the agent's realized level of income y_t is given by:

$$y_t = exp(\sigma\epsilon_t) \tag{1}$$

where ϵ_t is a standard normal random variable. We assume that a parsimonious, iid specification of the income process for simplicity. The agent makes use of both income and credit to facilitate their consumption each period. The agent has a single credit card with limit L and current balance b_t which evolves according to:

$$b_t = (1+r)b_{t-1} + \phi_{t-1} \tag{2}$$

where $\phi_t \in \Phi(b_t)$ and $\phi_t > 0$ denotes net borrowing while $\phi_t < 0$ denotes net repayment. r is the per-period interest rate. The feasible set of net borrowing is given by $\Phi(b_t) = [-(1+r)b_t, L-(1+r)b_t]$. In words, the most that the agent can repay is their full balance plus accrued interest $(1+r)b_t$, and the most they can borrow is their remaining credit $L-(1+r)b_t$.

Let $d_t \in \{0,1\}$ indicate whether the agent enters period t in delinquency. Conditional on not being delinquent ($d_t = 0$), the agent commits at the beginning of the period to either keep their account current or go delinquent in the next period. In other words, d_{t+1} is chosen at the beginning of period t. We assume log flow utility from consumption $u(c_t) = log(c_t)$,

where c_t is given by:

$$c_t = \begin{cases} y_t + \phi_t - (\pi + r)b_t & \text{if} \quad d_{t+1} = 0 \\ y_t + \phi_t & \text{if} \quad d_{t+1} = 1 \end{cases} \tag{3}$$

If the agent chooses to keep their account current, they make a minimum payment $(\pi + r)b_t$ and otherwise consume $y_t + \phi_t$. If the agent instead chooses to enter delinquency, they do not make the minimum payment. Following the choice of d_{t+1}, credit utilization decisions ϕ_t are made optimally.

If the agent enters the period delinquent ($d_t = 1$), the agent's balance is written off and they enter default with probability $p(b_t)$. We allow the likelihood of default to vary with the outstanding balance:

$$p(b_t) = 1 - exp(-(q_1 + q_2 b_t)) \tag{4}$$

where q_1 fixes the level of the default rate whereas q_2 measures the sensitivity of default to outstanding debt. This reflects the possibility that, for example, credit providers are more likely to write off large, delinquent balances than small ones. Upon default, the agent's terminal payoff is given by:

$$D(b_t) = -(\kappa + \alpha b_t) \tag{5}$$

where κ is a baseline cost of default and α measures the sensitivity of default costs to the defaulted amount. With probability $(1 - p(b_t))$, the agent does not default, and must again choose d_{t+1}, indicating their commitment to either exit delinquency or stay delinquent for another period.

2.1 Value Functions

The relevant state is (y_t, b_t, d_t). Conditional on not being delinquent, the agent makes a repayment decision satisfying the Bellman equation:

$$V(y_t, b_t, 0) = \max \left\{ V_{curr}(y_t, b_t, 0), V_{enter}(y_t, b_t, 0) \right\} \tag{6}$$

Equation (6) states that agents whose accounts are current begin period t by committing to either keeping their account current or entering delinquency in the next period. The corresponding conditional value functions are given by:

$$V_{curr}(y_t, b_t, 0) = \max_{\phi \in \Phi(b_t)} \left\{ u(y_t + \phi_t - (\pi + r)b_t) + \beta \mathbb{E}_t[V(y_{t+1}, b_{t+1}, 0)] \right\} \tag{7}$$

$$V_{enter}(y_t, b_t, 0) = \max_{\phi \in \Phi(b_t)} \left\{ u(y_t + \phi_t) + \beta \mathbb{E}_t[V(y_{t+1}, b_{t+1}, 1)] \right\} \tag{8}$$

If the agent elects to keep their account current, they make a minimum payment $(\pi + r)b_t$, make a credit utilization decision ϕ_t, and enter the next period with $d_{t+1} = 0$. If instead the agent commits to entering delinquency, they do not make the minimum payment, make a credit utilization decision, and enter the next period with $d_{t+1} = 1$.

Conditional on entering the period in delinquency, the agent's value is given by:

$$V(y_t, b_t, 1) = p(b_t)D(b_t) + (1 - p(b_t)) \max \left\{ V_{exit}(y_t, b_t, 1), V_{stay}(y_t, b_t, 1) \right\} \tag{9}$$

With probability $p(b_t)$, the agent's balance is written off and they enter default, upon which they pay the relevant default costs and cease any decision making. With probability $(1 - p(b_t))$, the agent decides whether to exit delinquency or stay delinquent for another period.

The conditional value functions are given by:

$$V_{exit}(y_t, b_t, 1) = \max_{\phi \in \Phi(b_t)} \left\{ u(y_t + \phi_t - (\pi + r)b_t - \lambda) + \beta \mathbb{E}_t[V(y_{t+1}, b_{t+1}, 0)] \right\} \tag{10}$$

$$V_{stay}(y_t, b_t, 1) = \max_{\phi \in \Phi(b_t)} \left\{ u(y_t + \phi_t) + \beta \mathbb{E}_t[V(y_{t+1}, b_{t+1}, 1)] \right\} \tag{11}$$

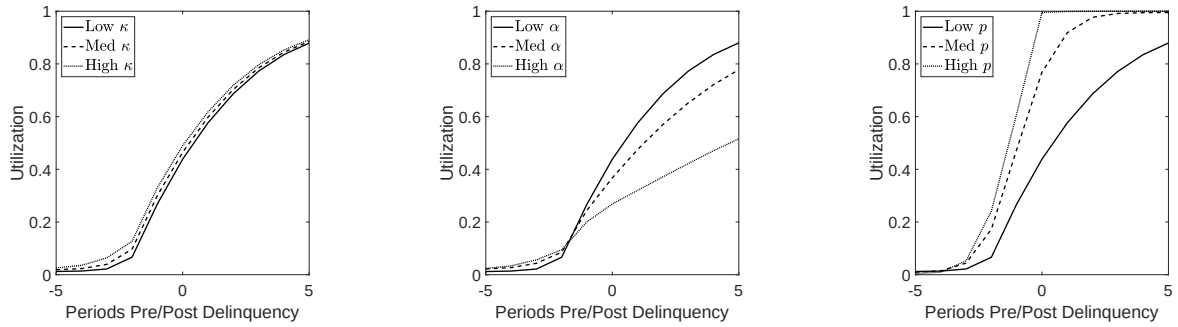
If the agent commits to exiting delinquency, they make the minimum payment $(\pi + r)b_t$ plus a late fee λ, make a credit utilization decision, and enter the next period with $d_{t+1} = 0$. If the agent instead commits to remaining delinquent, they do not make the minimum payment, make a credit utilization decision, and enter the next period with $d_{t+1} = 1$.

2.2 Comparative Statics

To illustrate to effect of the parameter values on credit utilization decisions, we report several comparative statics. The purpose of this exercise is twofold. First, we show that opportunistic borrowing before default is a robust feature of agents' optimal utilization policies. Second, we illustrate how agents' propensity to opportunistically borrow in anticipation of default varies with key model parameters. We focus specifically on the three parameters characterizing default: the fixed cost of default (κ), the sensitivity of default penalties to the borrowed amount (α), and the probability of default conditional on delinquency (q_1). We begin by analyzing the case with homogeneous default probabilities ($q_2 = 0$), in which the probability of default is independent of agents' outstanding balance. Afterwards, we introduce heterogeneous default risks to illustrate deviations in behavior between agents who eventually enter default and those who do not. In each case, we simulate the model and record optimal credit utilization for agents around their first instance of delinquency. We repeat this analysis under perturbations of the parameters (κ, α, p) to highlight the key economic forces driving agents' strategic borrowing behavior. All results are illustrated in Figure 1.

First, we examine the role of the fixed default cost κ. Panel (a) of Figure 1 plots agents' simulated credit utilization around delinquency under three values of κ. Utilization is close to identical in each of the three cases, suggesting that fixed default costs have minimal impact on borrowing patterns around delinquency. While fixed default costs affect the overall desirability of entering delinquency, they leave unchanged agents' incentives to utilize credit when delinquency is imminent. Of course, increasing κ deters agents from accumulating large balances in first place, decreasing their likelihood of delinquency and, therefore, default. However, conditional on delinquency, rational agents continue to increase their credit utilization irrespective of κ. In other words, the effect of fixed default penalties are restricted to the extensive margin (agents' decision to enter delinquency), and have no affect on the intensive margin (agents' utilization decisions once delinquent or opportunistic borrowing).

Figure 1: Comparative Statics - Homogeneous Default Risk ($q_2 = 0$)



(a) Default Cost Level (κ) (b) Default Cost Slope (α) (c) Default Probability (q_1)

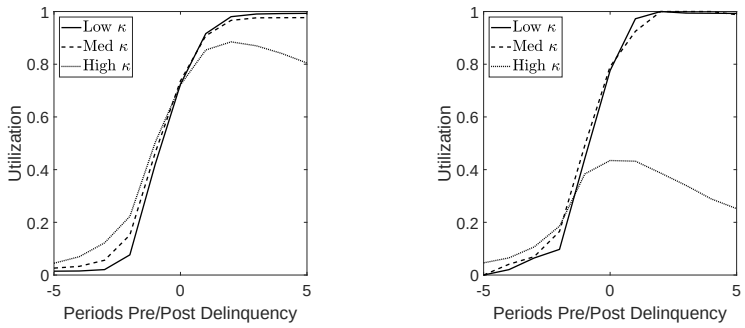
Notes: Figure 1 plots agents' simulated utilization decisions around their first episode of delinquency. Agents who never enter delinquency are therefore excluded from the figures. We repeat the model simulation under perturbations of each parameter (κ, α, p) to highlight their influence on agents' propensity to strategically borrow in anticipation of default.

Far more relevant is the sensitivity of default costs to the outstanding balance (α). As illustrated in Panel (b), increasing α significantly reduces opportunistic borrowing around delinquency. The economic intuition is straightforward: when default penalties increase with the outstanding balance, the marginal cost of additional borrowing rises sharply in the face of default risk. As α increases, agents rationally respond by restraining credit utilization to limit their balance in case of default.

Finally, we analyze the role of default risk, captured by the conditional default probability parameter q_1. Recall that 1 restricts attention to the simpler case with constant default risk ($q_2 = 0$); heterogeneity is introduced now. Panel (c) clearly demonstrates that increasing q_1 substantially amplifies agents' opportunistic borrowing. Economically, conditional on delinquency, if default is a near certainty (i.e. q_1 is high), agents can strategically anticipate default and extract maximum value from their credit line immediately prior to default. Conversely, as the risk of default declines, so does agents' incentive for opportunistic borrowing, as agents risk carrying unnecessary balances longer than intended. Thus, agents' expectations over the likelihood of entering default critically influence their propensity to opportunistically borrow.

We next move to the more realistic setting featuring heterogeneous default risk. In particular, we set $q_2 > 0$ so that delinquent agents are more likely to enter default as their outstanding balance increases. In this case, we highlight differences in observed credit utilization between agents whose balances are eventually written off relative to those who do not default, holding fixed the default risk function $p(b_t)$. Similar to the previous exercise, Figures 2 and 3 respectively plot simulated credit utilization around delinquency, separately for the two groups, as we vary the default penalty parameters κ and α.

Figure 2: Comparative Statics (κ) - Heterogeneous Default Risk ($q_2 > 0$)

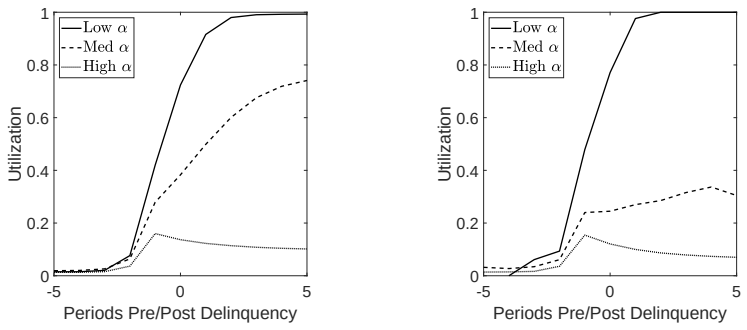


(a) Written Off (b) Not Written Off

We begin by analyzing the effect of the fixed default cost κ (Figure 2). There are several pat-

terns of note. First, agents who eventually default have a tendency to carry larger balances into delinquency. This is a mechanical artifact of the specification of $p(b_t)$. As the risk of default increases agents' balances, high-balance agents are selected into the "written off" category more often than low-balance agents. Hence, if default risk is endogenous, non-random selection induces differences in observed borrowing between agents who eventually default and those who do not. This across-group difference in observed utilization is amplified as default penalties increase. Additionally, recall that in the case with homogeneous default risk, κ had virtually no impact on agents' utilization decisions around delinquency (Panel (a) of Figure 1). With heterogeneous default risk, this is no longer the case. When default probabilities are homogeneous, and therefore independent of the outstanding balance, the fixed default cost only affects agents' extensive margin (the initial decision to enter delinquency), but does not influence borrowing incentives once delinquency is imminent. In contrast, when default probabilities are endogenous, higher balances directly raise the likelihood of default and thus amplify the expected cost imposed by the fixed penalty. Consequently, in the heterogeneous default risk scenario, agents rationally moderate their borrowing around delinquency to avoid larger balances as κ increases.

Figure 3: Comparative Statics (α) - Heterogeneous Default Risk ($q_2 > 0$)



(a) Written Off (b) Not Written Off

Figure 3 plots optimal utilization as the slope of the default penalty (α) increases, again separating agents who eventually enter default from those who do not. As in the homogeneous case (Panel (b) of Figure 1), balances carried into delinquency generally decrease with

respect to α. This deterrent effect is especially pronounced for agents who do not default eventually. These borrowers, anticipating that high balances significantly elevate expected costs if default occurs, become particularly cautious around delinquency. The heightened caution among borrowers who manage to avoid eventual default suggests a powerful selection effect: individuals who restrain their borrowing precisely because of escalating marginal penalties are more likely to successfully exit delinquency. Conversely, borrowers who eventually default moderate their borrowing less in response to increases in α, in part because they are already committed to larger outstanding balances, increasing their default probability. Thus, while endogenous default risk magnifies the strategic role of balance-dependent default penalties, it also introduces important selection dynamics, clearly separating borrowers by their ultimate default outcomes.

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 $CD_{t+1} > 0$.[4] 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 $Discretionary\ spending_t - Repayment_t$) 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* ($\frac{ClosingBalance_t}{Credit\ Limit_t}$) is on average 74.7%, which implies a £1,231.3 of *Credit Available* on each card ($CreditLimit_t - OpeningBalance_t - ChargesFees_t$).[5] *Net utilization* ($\frac{Net\ borrowing_t}{Credit\ available_t}$) is on average -25.4%, 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

[4]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.

[5]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 *Credit Available* to zero when this happens.

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

Let i index borrowers, j credit cards, and t billing–cycle months. Our main regression specification is as follows:

$$
\begin{aligned}
\textit{Net Borrowing}_{ijt} = {} & \beta_0 \textit{Credit Avail}_{ijt} + \beta_1 \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \\
& + \beta_2 \textit{Pre(-3,-1)}_{ijt} \times \textit{Credit Avail}_{ijt} + \beta_3 \textit{Pre(-3,-1)}_{ijt} \times \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \\
& + \beta_4 \textit{Post(0-6)}_{ijt} \times \textit{Credit Avail}_{ijt} + \beta_5 \textit{Post(0-6)}_{ijt} \times \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \\
& + \beta_6 \textit{Post(>6)}_{ijt} \times \textit{Credit Avail}_{ijt} + \beta_7 \textit{Post(>6)}_{ijt} \times \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \\
& + \textit{Delinq Aligned}_{ij} \Big[\delta_0 \textit{Credit Avail}_{ijt} + \delta_1 \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \\
& \qquad + \delta_2 \textit{Pre(-3,-1)}_{ijt} \times \textit{Credit Avail}_{ijt} \\
& \qquad + \delta_3 \textit{Pre(-3,-1)}_{ijt} \times \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \\
& \qquad + \delta_4 \textit{Post(0-6)}_{ijt} \times \textit{Credit Avail}_{ijt} \\
& \qquad + \delta_5 \textit{Post(0-6)}_{ijt} \times \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \\
& \qquad + \delta_6 \textit{Post(>6)}_{ijt} \times \textit{Credit Avail}_{ijt} \\
& \qquad + \delta_7 \textit{Post(>6)}_{ijt} \times \textit{Charged-Off}_{ij} \times \textit{Credit Avail}_{ijt} \Big] \\
& + \boldsymbol{\zeta}^\top \mathbf{X}_{ijt} + \alpha_{it} + \varepsilon_{ijt}. \qquad (12)
\end{aligned}
$$

$\textit{Net Borrowing}_{ijt}$ is discretionary borrowing (i.e., borrowing excluding fees) minus repayment

in month t on card j. *Credit Avail*$_{ijt}$ is credit available, which equals the end–of–month credit limit less the beginning-of-month balance and the charges and fees billed in month t, truncated at zero if negative. *Charged-Off*$_{ij}$ is an indicator that equals 1 if card j is ultimately charged off (after entering delinquency) during the sample, and 0 otherwise.

Denote by τ_{ij} the first month in which card j held by borrower i becomes delinquent (we require two consecutive missed minimum payments). The time indicators are as follows: *Pre(-3,-1)*$_{ijt} = 1$ for the three months preceding delinquency, i.e., $t \in \{\tau_{ij}-3, \tau_{ij}-2, \tau_{ij}-1\}$; *Post(0-6)*$_{ijt} = 1$ for months $t \in \{\tau_{ij}, \tau_{ij}+1, \ldots, \tau_{ij}+6\}$ (0–6 months after delinquency); *Post(>6)*$_{ijtjt} = 1$ for $t \geq \tau_{ij}+7$; months $t \leq \tau_{ij}-4$ form the omitted category.

The alignment indicator *Delinq Aligned*$_{ij}$ equals 1 if, in month τ_{ij}, borrower i becomes *newly delinquent* on more than one card and at least one—but not all—of those simultaneously delinquent cards is ultimately charged off. We also require that borrower i has *no prior charge-off* on any card before τ_{ij}. If these conditions are not met, then *Delinq Aligned*$_{ij} = 0$.

$\mathbf{X}_{ijt}$ collects the additional interactions that are not shown here for brevity. α_{it} are borrower$\times$ year-month fixed effects that absorb time–varying shocks common to all cards held by borrower i in month t. In all our models, standard errors are two–way clustered by borrower and calendar month.

The alignment restriction embodied in *Delinq Aligned*$_{ij} = 1$ is central to our identification strategy. By requiring no prior charge-off before the month τ_{ij} in which card j first becomes delinquent, we preserve a clean pre-delinquency comparison window: earlier default events could tighten credit limits, raise fees, or otherwise alter borrower repayment incentives in ways that would confound the interpretation of borrowing behavior. Moreover, because *Delinq Aligned*$_{ij} = 1$ stipulates that borrower i becomes *newly* delinquent on *multiple cards* in the *same* calendar month, we are comparing borrowing behavior across cards that are exposed to the same borrower–month shock. With borrower$\times$month fixed

effects α_{it} in Eq. (12), any unobserved liquidity, income, or information shock that triggered the simultaneous missed payments is absorbed, so within these aligned episodes, differences in post-delinquency borrowing responses across cards that are eventually charged off (DD cards) versus those that remain current (DO cards) cannot be attributed to borrower-specific factors but instead reflect within-borrower card-specific behavior.

Retaining non-aligned delinquencies alongside aligned ones preserves statistical power. Aligned episodes are a small, highly selected slice of the data, so dropping the rest would significantly reduce sample size and inflate standard errors, making slope estimates for the charged-off cards imprecise. Moreover, interacting every term with the alignment indicator rather than conditioning on it allows us to difference aligned against non-aligned episodes within the same regression, thereby purging borrower-month shocks that hit all cards simultaneously, which allows us to test for differences in borrowing behavior between DD and DO cards that face the same income shock.

Under opportunistic borrowing, once a borrower crosses into delinquency on multiple cards in the same month, she should draw down available credit on DD cards, but not on DO cards. Our estimating equation (Eq. 12) allows the sensitivity of net borrowing to credit available to vary (i) across relative time windows (pre vs. post), (ii) by eventual charge–off status $\textit{Charged-Off}_{ij}$ (DD vs. DO cards), and (iii) differentially for aligned cards $\textit{Delinq Aligned}_{ij} = 1$ through the δ coefficients. Because the alignment restriction differences out the common borrower shock via α_{it}, the post–delinquency slope on credit available for aligned, charged–off cards provides a direct test of the opportunistic borrowing hypothesis.

$$\Theta_{co}^{\text{post}}(A) \;=\; \frac{\partial \textit{Net Borrowing}_{ijt}}{\partial \textit{Credit Avail}_{ijt}}\Bigg| \textit{Post(0-6)}_{ijt} = 1,\ \textit{Charged-Off}_{ij} = co,\ \textit{Delinq Aligned}_{ij} = A,$$

denote the post–delinquency (0-6 months) credit sensitivity for cards with charge–off status $co \in \{DO = 0, DD = 1\}$ and alignment status $A \in \{0, 1\}$. From Eq. (12),

$$\Theta^{\text{post}}_{DO}(A = 1) = (\beta_0 + \beta_4) + (\delta_0 + \delta_4), \tag{13}$$

$$\Theta^{\text{post}}_{DD}(A = 1) = (\beta_0 + \beta_1 + \beta_4 + \beta_5) + (\delta_0 + \delta_1 + \delta_4 + \delta_5). \tag{14}$$

The within–aligned difference in the sensitivity of net borrowing to credit available for cards that are eventually charged off (DD) versus those that cure (DO) in the Post(0–6) window is

$$\begin{aligned} \Delta\Theta^{\text{post}}_{\text{DD–DO}}(A = 1) &= \Theta^{\text{post}}_{\text{DD}}(A = 1) - \Theta^{\text{post}}_{\text{DO}}(A = 1) \\ &= (\beta_1 + \beta_5) + (\delta_1 + \delta_5). \end{aligned} \tag{15}$$

Strong Opportunistic Borrowing (max-out). If borrowers fully exploit available credit on the cards they will not repay, then in aligned episodes the post-delinquency slope of net borrowing on available credit for DD cards equals one:

$$H_0^{\text{strong}} : \ \Theta^{\text{post}}_{\text{DD}}(A = 1) = 1.$$

Weak Opportunistic Borrowing. Strategic behavior requires that borrowers draw *more* against available credit on DD than on DO cards within aligned episodes:

$$H_0^{\text{weak}} : \ \Delta\Theta^{\text{post}}_{\text{DD–DO}}(A = 1) \leq 0 \qquad \text{vs.} \qquad H_1 : \ \Delta\Theta^{\text{post}}_{\text{DD–DO}}(A = 1) > 0.$$

The two hypotheses are nested. Failing to reject H_0^{weak} rules out strategic borrowing altogether. Rejecting H_0^{weak} but not H_0^{strong} implies partial (but not full) pre-default drawdown

of available credit. We report estimates of $\widehat{\Theta}^{\text{post}}_{DO}(A = 1)$, $\widehat{\Theta}^{\text{post}}_{DD}(A = 1)$, their difference $\Delta\Theta^{\text{post}}_{\text{DD–DO}}(A = 1)$, and F-tests of both H_0^{strong} and H_0^{weak}.

4 Results

4.1 Baseline Analysis

Table 2 shows the results when estimating Equation **??**. 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* $\times$ *Charged-off card* $\times$ *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* × *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* × *Charged-off card* × *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 7. 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 **??**. 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 **??**. 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* $\times$ *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 af-*

ter delinquency × *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 6, 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 **??**). 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*× *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* × *Charged-off card* × *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 3 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 5 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 8 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.[6] As shown in Figure 7, 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 8 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%.[7] 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.[8] 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

[6]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.

[7]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.

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

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 **??** 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.

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.[9]

However, many people who default on their credit card debt are unlikely to own any significant assets.[10] Recovery rates for credit card debt are around 25%.[11] The length of time a debt collector can chase a defaulter for a debt in the UK is governed by the Limitation Act

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

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

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

(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.[12] 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.[13]

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.

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.

[12] See https://ukdebtexpert.co.uk/knowledge-hub/when-do-debt-collectors-give-up/.
[13] See https://www.experian.co.uk/consumer/guides/defaults.html.

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.

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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: Testing for Opportunistic Borrowing

	(1) Max-out hypothetical net borrowing	(2) Actual net borrowing
Credit Avail	0.054***	0.054***
	(0.002)	(0.002)
Charged-off × Credit Avail	0.013***	0.013***
	(0.004)	(0.004)
Post (0-6) × Credit Avail	-0.037***	-0.037***
	(0.002)	(0.002)
Post(0-6) × Charged-off × Credit Avail	-0.016***	-0.016***
	(0.004)	(0.004)
Delinq Aligned × Credit Avail	0.019***	0.019***
	(0.006)	(0.006)
Delinq Aligned × Charged-off × Credit Avail	-0.012	-0.012
	(0.009)	(0.009)
Delinq Aligned × Post(0-6) × Credit Avail	-0.035***	-0.026***
	(0.007)	(0.007)
Delinq Aligned × Post(0-6) × Charged-off × Credit Avail	1.015***	0.013
	(0.009)	(0.011)
Individual × month-by-year fixed effects	✓	✓
Observations	287,379	287,368
Adj. R^2	0.220	0.144
Strong Opportunistic Borrowing: $\Theta^{\text{post}}_{\text{DD}}(DA=1)=1$	1.000	0.007
Strong Opportunistic Borrowing p-value	0.447	0.000
Weak Opportunistic Borrowing: $\Delta\Theta^{\text{post}}_{\text{DD–DO}}(DA=1)>0$	0.999	-0.003
Weak Opportunistic Borrowing p-value (one-sided)	0.000	0.695

This table presents our main results. 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 Avail* 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 Avail* 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* is set to 1 if a card that enters delinquency is eventually charged-off. We set the indicator *Delinq Aligned* 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. *Post(0-6)* is an indicator that equals 1 for the months from t to $t+6$, where $t=0$ is the month that delinquency starts. In Column (1) we calculate *Net borrowing* in a hypothetical scenario where, for the cases where *Delinq Aligned=1*, borrowers max-out cards that entered delinquency in month $t=0$ that were eventually charged-off (DD cards) in our sample (i.e., borrowed up to the credit limit on that card in month $t+1$) and have zero borrowing on cards that entered delinquency in that same month but where not eventually charged off (DO cards). In Column (2) we estimate the same model using the actual *Net borrowing* variable. The last two rows present the coefficients and p-values from F-statistics that underlie strong and weak opportunistic borrowing. Strong opportunistic borrowing implies that the coefficient on credit available for aligned (*Delinq Aligned (DA)=1*), charged off cards (DD), in post delinquency periods equals 1. Weak opportunistic borrowing implies that, for aligned cards, the difference in the coefficients on credit available between charged off and delinquent only cards (DD vs. DO cards) is positive, and the table shows the corresponding p-value form a one-sided test. 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
IG × Credit Avail × Charged-off	-0.038**	0.004	0.015	0.002
	(0.018)	(0.007)	(0.009)	(0.006)
IG × Credit Avail × Charged-off × Delinq Aligned	-0.047	-0.019	-0.059**	-0.012
	(0.029)	(0.018)	(0.027)	(0.020)
IG × Credit Avail × Charged-off × Post(0–6)	-0.006	-0.006	-0.032***	-0.005
	(0.056)	(0.007)	(0.011)	(0.009)
IG × Credit Avail × Charged-off × Post(0–6) × Delinq Aligned	0.026	0.016	0.051	0.005
	(0.074)	(0.022)	(0.031)	(0.021)
IG Variable	Above median utilization	Above median revolving balance	Above median minimum payment	Above median holding time
Individual × month-by-year fixed effects	✓	✓	✓	✓
Observations	287,368	287,368	287,368	287,368
Adj. R^2	0.294	0.148	0.153	0.150
$\Delta\Theta^{\text{post}}_{\text{DD–DO}}(DA{=}1)\big\vert_{IG=1} - \Delta\Theta^{\text{post}}_{\text{DD–DO}}(DA{=}1)\big\vert_{IG=0} = 0$	-0.066	-0.005	-0.025	-0.009
p-value (two-sided)	0.157	0.681	0.156	0.278

This table examines for a difference in weak-form opportunistic borrowing depending on an indicator variable (IG), which takes the value of 1 if a specific variable for card i in month t is above the sample median and 0 otherwise. In Column (1) the variable is utilization, in Column (2) revolving balance, in Column (3) minimum payment, and in Column (4) the holding time of the specific credit card (since the card was first obtained). Variable definitions and sample construction criteria are as in Table 2. The table presents the four coefficients that show the difference in weak opportunistic borrowing across IG groups. The last two rows in the table present the point estimate of this difference and the associated p-value. 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***	-0.037***
	(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)
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	-0.011	-0.011
	(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	0.012
	(0.011)	(0.011)
Individual × month-by-year × stack fixed effects	✓	✓
Observations	5,644,891	5,643,356
Adjusted R^2	0.145	0.000

This table presents the same analysis as Table **??** when we use a clean-control estimating procedure where we create one stack for each treatment (*Delinquencies of* $N > 1$ *cards and* $N > n > 1$ *charged off*) using only clean controls, i.e., individuals that did not have such an event over the sample period. Variable definitions and sample construction criteria are as in Table **??**. 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: 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 × 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 × 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 7: Comparison of all Defaulters to those that were Delinquent on Multiple Cards Simultaneously

	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

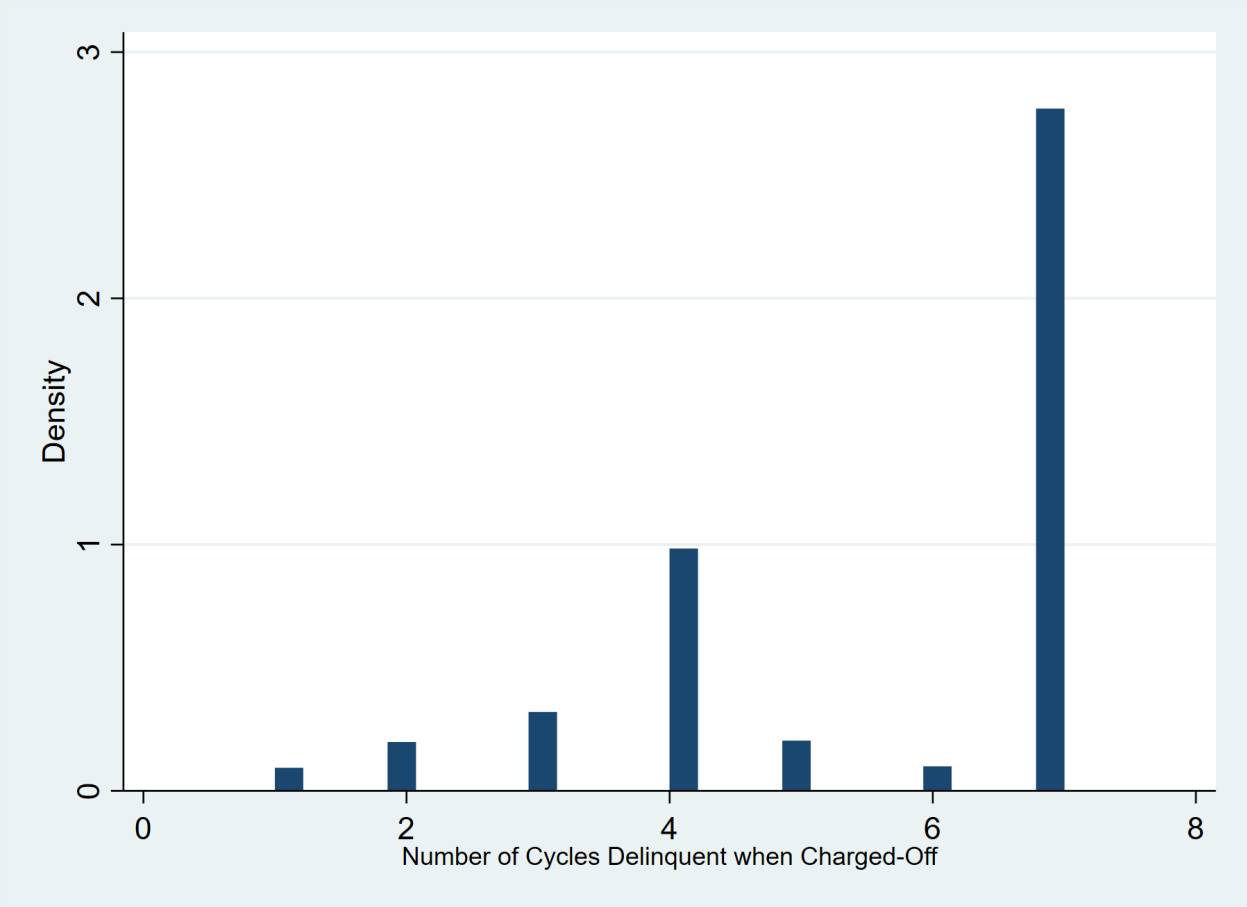
This table presents a covariance balance test, comparing various credit card variables between borrowers who go delinquent on multiple cards simultaneously and delinquent borrowers in our overall sample, who can go delinquent on different cards in different months.

Table 8: 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

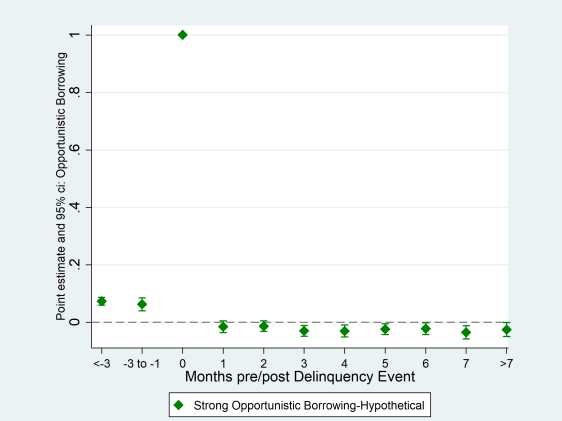
This table presents the results of predicting which card will default using different sets of card-specific variables.

Figure 1: Months Delinquent at Charge-Off

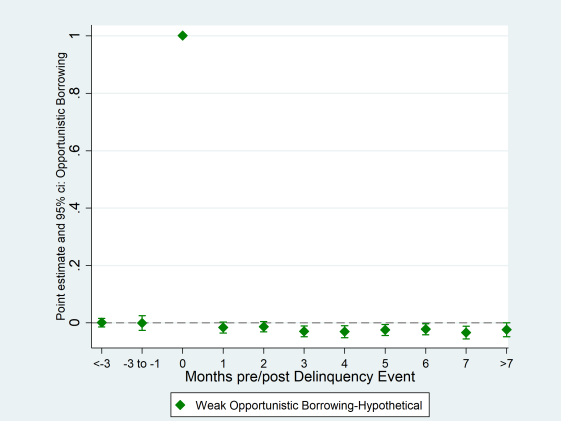


This figure shows the number of months a card is delinquent before being charged off by the credit card provider.

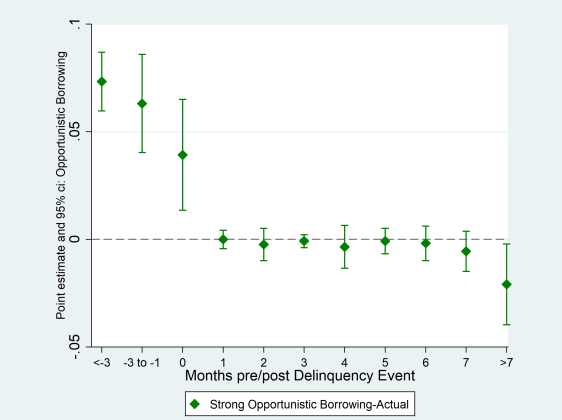
Figure 2: Tests of Opportunistic Borrowing Around Delinquency



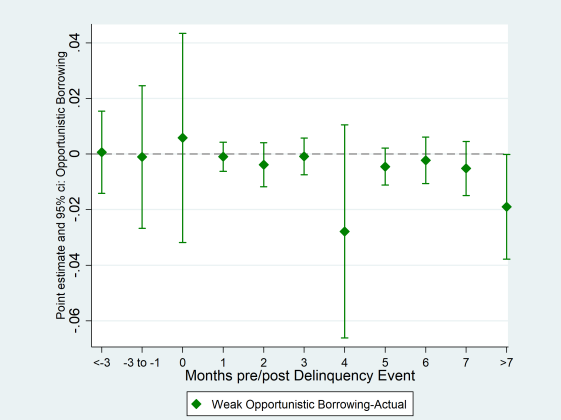
(A): Strong Test:Hypothetical



(B): Weak Test: Hypothetical



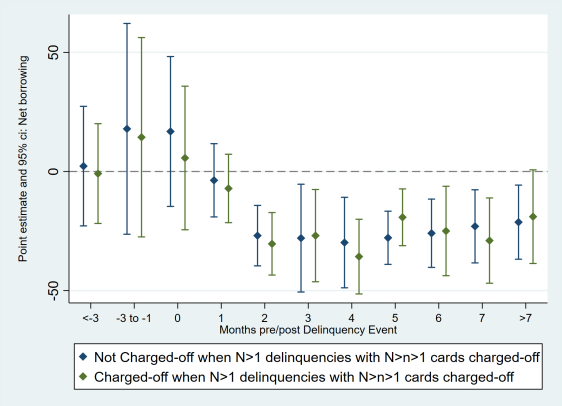
(C): Strong Test: Actual



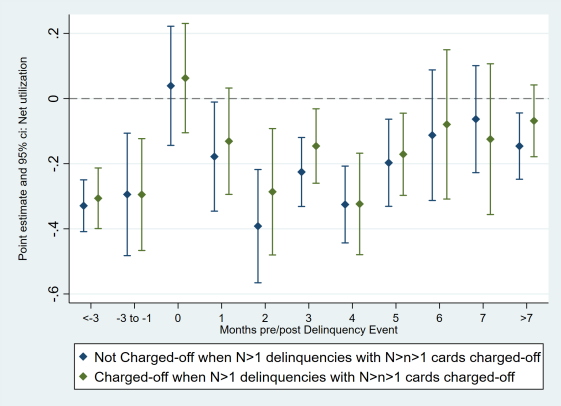
(D): Weak Test: Actual

These figures show tests of the strong and weak opportunistic borrowing hypotheses using in each month around the start of delinquency for hypothetical and actual data (as in Table 2). The definition of the strong and weak opportunistic borrowing tests are shown in the the last 4 rows of Table 2. The displayed standard error bars are obtained by clustering at the individual and month-by-year levels.

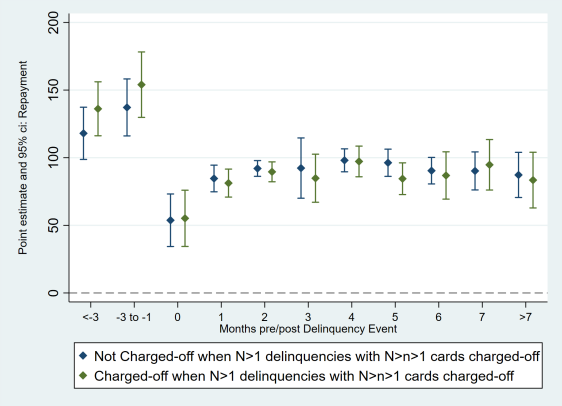
Figure 3: Margin plots Utilization and Net Utilization around Delinquency



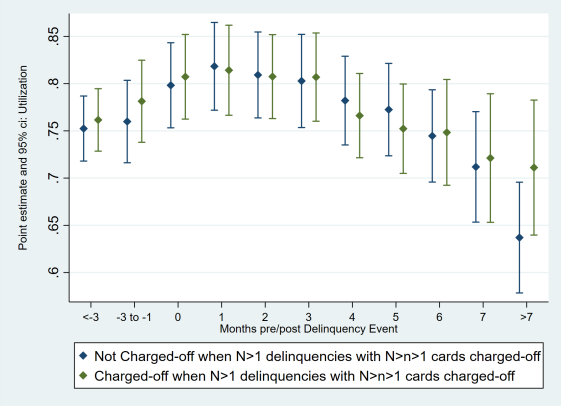
(A): Net borrowing



(B): Net utilization



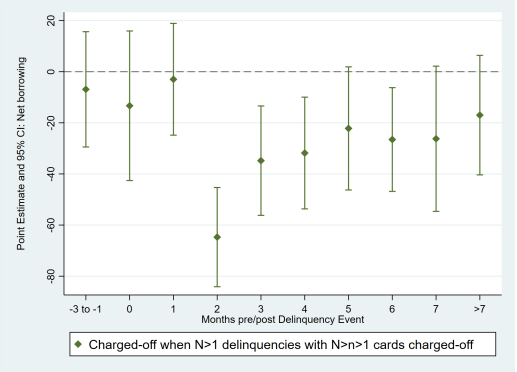
(C): Repayment



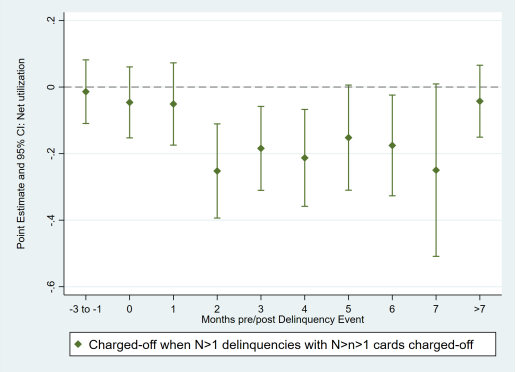
(D): Utilization

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.

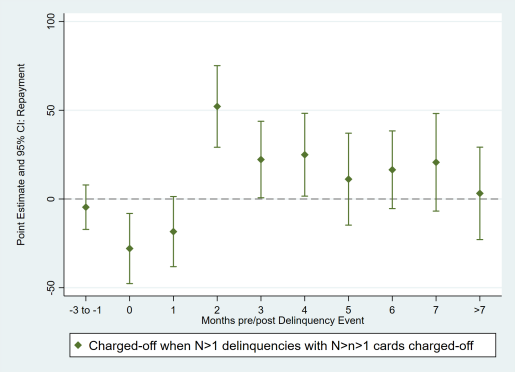
Figure 4: Dynamic Analysis of Credit Card Outcomes around Delinquency



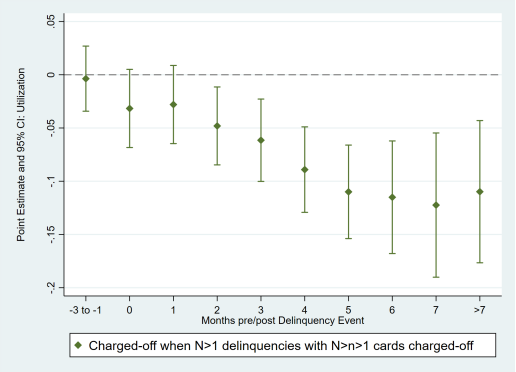
(A): Net borrowing



(B): Net utilization



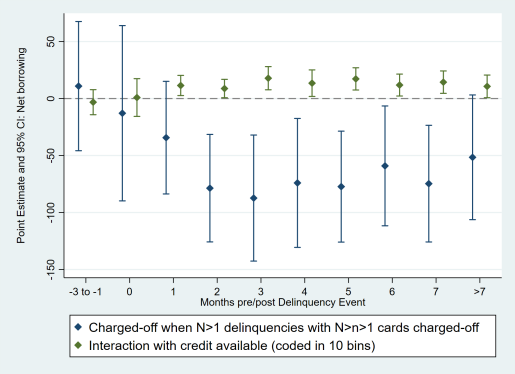
(D): Repayment



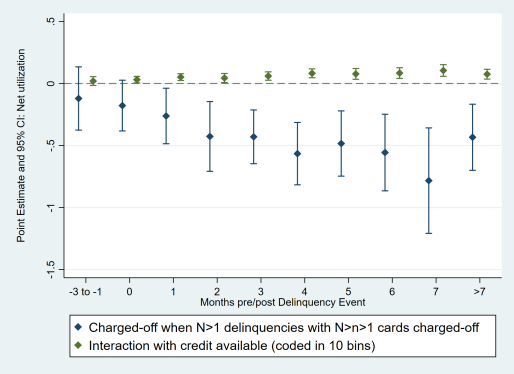
(D): Utilization

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.

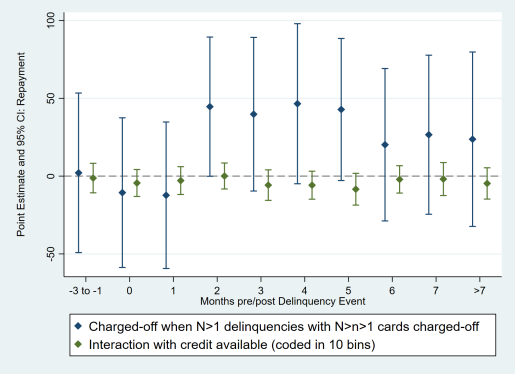
Figure 5: Dynamic Analysis of Credit Card Outcomes around Delinquency: Interactions with Credit Available



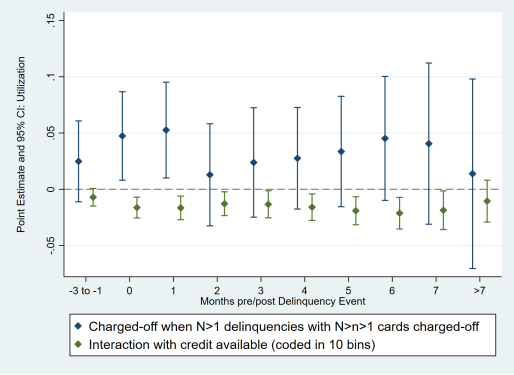
(A): Net borrowing



(B): Net utilization



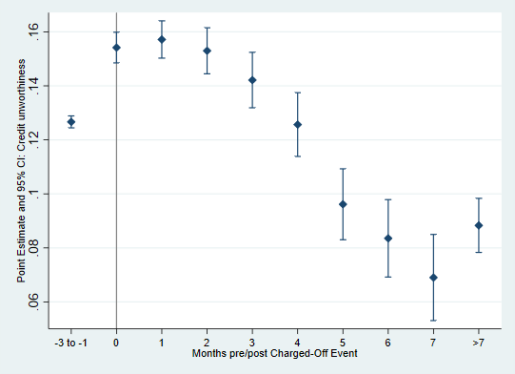
(D): Repayment



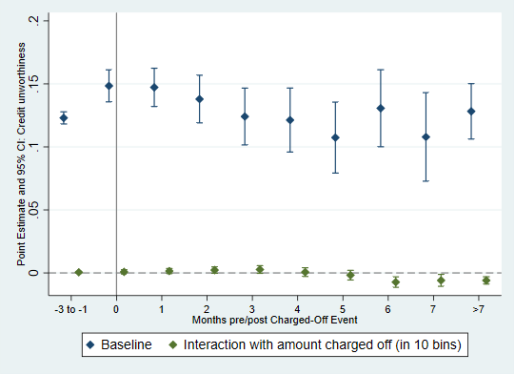
(D): Utilization

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 including the interaction with credit available (coded in ten bins). 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.

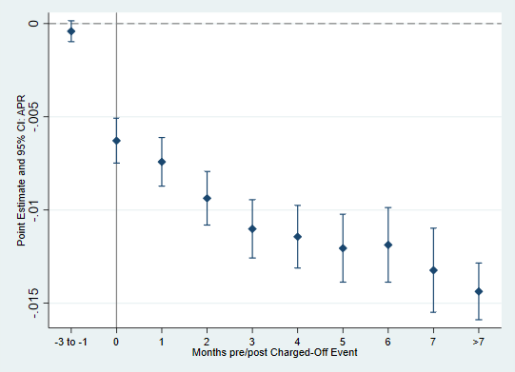
Figure 6: Dynamic Analysis of Credit Scores, APRs, and Limits around Charge-Off



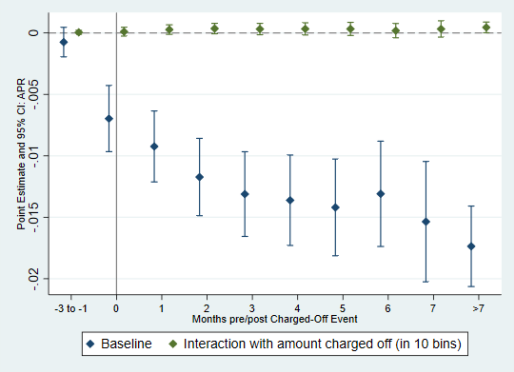
(A): Charge-off rate



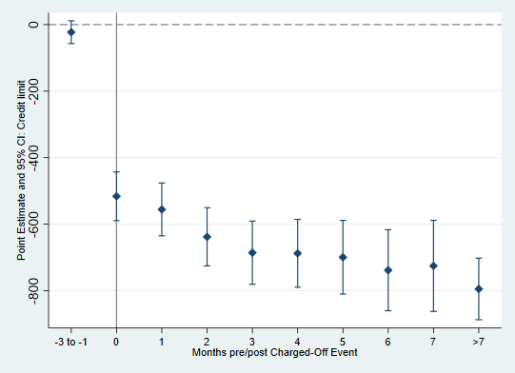
(B): Charge-off rate



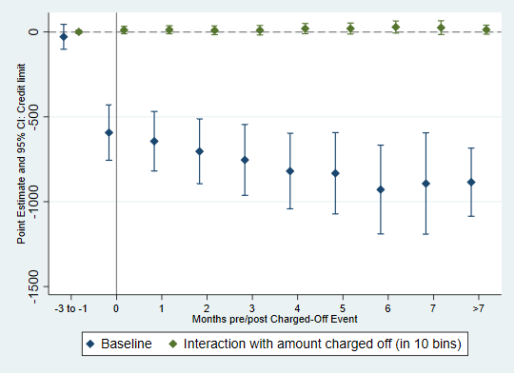
(C): APRs



(D): APRs



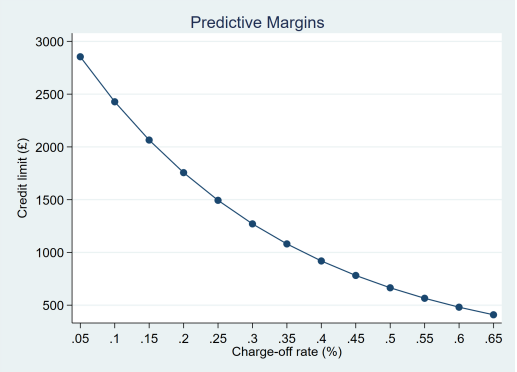
(E): Credit limits



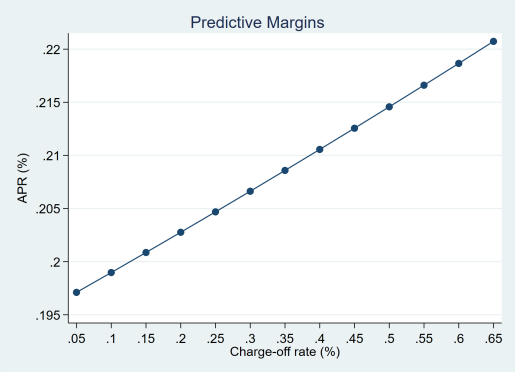
(F): Credit limits

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 left side, the figures show the coefficients on the time dummies before and after delinquency. 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 *Credit 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 7: Charged-off rate, Credit Limit and APR



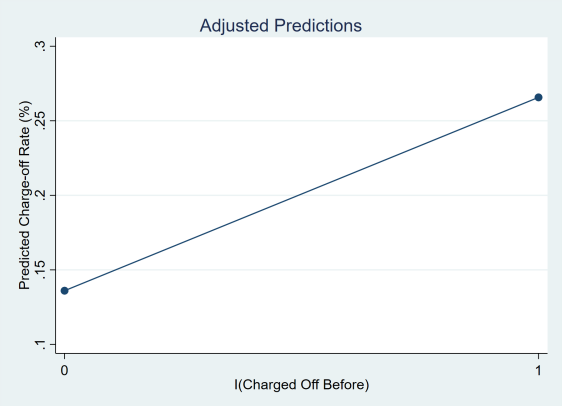
(A): Credit Limit



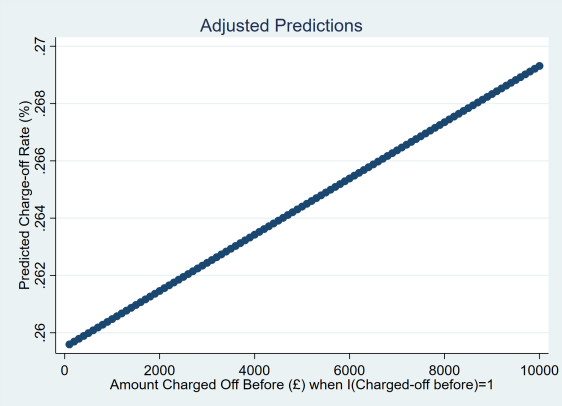
(B): APR

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 8: 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.