Opportunistic Borrowing in the Credit Card Market*

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Abstract

Credit card delinquencies and default may be a form of insurance for poorer households. This brings about potential for moral hazard: do credit card holders borrow opportunistically prior to defaulting on their credit card debt? To answer this question in a cleanly identified setting, we focus on borrowers who go delinquent on multiple credit cards simultaneously, with some of them eventually being charged off. We can then control for all unobserved time-variant borrower-specific factors that influence delinquency and default using borrower-by-billing-cycle (year-month) fixed effects. In this setting, we find no evidence that users borrow more or repay less on the delinquent cards that are ultimately charged off versus those that are not. We then show in a structural model that agents must believe that the sensitivity of default penalties to the borrowed amounts are very large. This is not consistent with, first, low recovery rates in the debt collection market, and second, additional evidence showing that the defaulted debt amounts have no impact on credit scores, limits, or APRs.

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

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1 Introduction

The credit card market is widely viewed as being highly profitable for issuers and as tending to redistribute from lower-income users to more affluent users. Issuers collect high interest charges, fees, and penalties, primarily from poorer borrowers [Ausubel, 1991], and more affluent borrowers disproportionately gain from rewards [Agarwal et al., 2023]. Additionally, the presence of merchant and interchange fees implies a large redistribution from cash users to card users (see Schuh [2010] and Egan et al. [2025]). Finally, credit card providers engage in co-branding with, e.g., airlines and hotels, which has additional redistributive effects that are likely to be regressive.

On the other hand, credit card debt is the largest position of unsecured debt on household balance sheets and delinquencies or defaults could be a form of insurance that the credit card market provides to poorer households. In the fourth quarter of 2024, more than $1 trillion in credit card debt was outstanding, with 3.23% of credit cards becoming delinquent, and 4.69% of the debt being ultimately charged off.[1] This amounts to $47 billion, which vastly exceeds conventional social insurance payouts like unemployment benefits standing at $8.69 billion in that quarter.[2] The option to default on credit cards may thus serve as a *de facto* private insurance mechanism, which could induce moral hazard by weakening the incentive to repay when the costs of defaulting do not outweigh the benefits of staying current. Given both the large outstanding credit card balances on household balance sheets and the substantial volume of charged-off debt each quarter, we are thus interested in 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.

[1] For historical comparison, the delinquency rate peaked during the financial crisis in 2009, at 6.77% with 10.54% of that debt being charged off.

[2] See the Delinquency Rate on Credit Card Loans, All Commercial Banks, FRED Economic Data. For the amount of unemployment benefits, see Statista https://www.statista.com/statistics/284857/total-unemployment-benefits-paid-in-the-us/.

[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 around delinquency and default: *opportunistic borrowing* on credit cards that are eventually written off.

Opportunistic borrowing occurs when borrowers, anticipating that they may default on a given card and low recovery rates in debt collection, 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. The credit card industry is concerned about such borrowing.[3] If such borrowing is widespread, it would add an important new dimension to strategic defaults, beyond the commonly studied choice of continuing or stopping repayments. At the same time, the absence of opportunistic borrowing would also be informative, suggesting that borrowers perceive high marginal costs of defaulting on additional borrowing that deter them from exploiting available credit; or that behavioral factors—such as norms against "maxing out" before default, fairness considerations toward lenders, or overoptimistic beliefs about curing delinquent cards—constrain strategic behavior. More broadly, whether or not such borrowing occurs provides valuable insight into borrowers' attitudes toward debt and repayment once they are already in financial distress. To the best of our knowledge, this study is the first to use a rich panel of consumer-level credit-card data as well as a structural model to study the dynamics of borrowing around delinquency and default and provide the first evidence on whether (and

[3]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.

why) consumers do–or do not–engage in opportunistic borrowing.

We 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 affect delinquencies, spending, borrowing, and repayment. 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 $NetBorrowing_{ijt}$, defined as $Discretionary\ Spending_{jt} - Repayment_{jt}$ measured on card j in month t. The key independent variables are: $Post(0\text{-}7)_{ijt}$, which equals 1 in the seven months after card j enters delinquency; $ChargedOff_{ij}$, which

equals 1 if card j is a DD card that is eventually charged off; and $SyncedDelinqs_{ij}$, which equals 1 if borrower i entered delinquency on card j in the same month as other cards and some but not all of them were ultimately charged off. Our DD–DO comparisons focus on synchronous delinquency cases, which ensure that the income shock that sends borrowers into delinquency shock is common across card types.

The main regressor of interest is credit available ($CreditAvail_{ijt}$) on card j in month t. The coefficient on this variable captures the sensitivity of $NetBorrowing_{ijt}$ to $CreditAvail_{ijt}$. We estimate the model by interacting all the independent variables, and then use the estimated coefficients to recover the sensitivity of $NetBorrowing_{ijt}$ to $CreditAvail_{ijt}$ for DD versus DO cards when $Post(0\text{-}7)_{ijt} = 1$ and $SyncedDelinqs_{ij} = 1$, i.e., during the post-delinquency months in cases where multiple cards went delinquent at the same time and some but not all of them were eventually charged off.

We test two versions of the opportunistic borrowing hypothesis: The *Strong Opportunistic Borrowing* test is that the coefficient on $CreditAvail_{ijt}$ conditional on $Post(0\text{-}7)_{ijt} = 1$ and $SyncedDelinqs_{ij} = 1$ equals one, 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 Opportunistic Borrowing* test is that the difference in the slopes between DD and DO cards, conditional on $Post(0\text{-}7)_{ijt} = 1$ and $SyncedDelinqs_{ij} = 1$ is positive and significant, indicating a stronger propensity to draw down available credit on DD cards.

We find no evidence of opportunistic borrowing in the data. 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 strong opportunistic borrowing. Furthermore, under the weak opportunistic borrowing hypothesis, the difference in slopes between DD and DO cards is -0.003, statistically indistinguishable from zero, but tightly estimated.

We also analyze the dynamic patterns of net borrowing, repayment, utilization, and net utilization (defined as $NetBorrowing_{ijt}/CreditAvail_{ijt}$) around (synchronous) delinquencies for DO and DD cards. We find that net borrowing and net utilization are negative for both types of cards after delinquencies. Repayment drops relative to pre-delinquency months, but remains positive, which means that borrowers continue to make payments after delinquencies. Utilization rises slightly after delinquencies, 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 implies the absence of opportunistic borrowing. In synchronous delinquency episodes, DD and DO cards exhibit statistically indistinguishable post-delinquency behavior in terms of borrowing and repayment. Moreover, we document a broad reduction in net borrowing across both DD and DO 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 answer three additional open questions related to the costs and benefits of opportunistic borrowing. First, can borrowers predict which card they default on? Second, how much money is "left" on the table on 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 conduct predictability regressions using card-specific information, such as minimum payment amounts, up to the point of delinquency, and show that there is significant predictability, which suggests that borrowers can predict with reasonable confidence which cards will eventually default. As for the second question, as already mentioned, we document that roughly 0.15×4.8K=£721 could be borrowed opportunistically.

With regards to 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*.[4] We find that, although defaulting on a card significantly raises a borrower's *Charged-off rate* for other cards, the amount defaulted does not materially exacerbate this. Beyond the *Charged-off rate*, we also show that, even though the credit limits on other cards drop significantly when a default on another card happens (in line with a worsening of borrowing conditions), credit limits are not sensitive to the defaulted amount.[5] Thus, the explanation that opportunistic borrowing does not occur because of potentially higher additional default costs is not supported by the data.

Why do we not observe opportunistic borrowing? To answer this question, we examine agents' borrowing behavior through the lens of a structural model. Mirroring the empirical analysis, agents in the model hold multiple credit cards and may go delinquent on any number of them. In response to liquidity shocks, agents make forward-looking decisions over whether to finance consumption via liquid wealth or additional credit card spending, potentially using a soon-to-default card. In case of default, agents incur balance-dependent penalties, the parameters of which we interpret as agents' subjective, possibly-misspecified beliefs about default costs.

We estimate the model via General Methods of Moments (GMM) taking our reduced-form estimates as direct estimation inputs. Our estimates imply that agents' perceived cost of default is substantially affected by the defaulted balance: agents behave as if defaulting on £1 costs £2.17 in consumption-equivalent units. These subjective default costs are difficult

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

[5] We also look at APRs but do not find strong effects consistent with the evidence in Matcham [2025] argueing that in the UK regulatory restrictions prevent credit card issuers from tailoring interest rates based upon default risk (though credit limits can be individually tailored).

to square with the institutional reality that (1) post-default credit score penalties do not scale with the defaulted amount and (2) post-default recovery rates are negligible. Our results therefore point towards agents having misspecified beliefs about "what happens" following default.

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 probabilities after delinquency are the same as observed in the data, borrowers max-out their cards before 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. However, in the model, whenever there is some probability to be written off at each cycle of delinquency, and that probability amounts to 100% at cycle 7, then the agent will be inclined to max-out the card before default.

The next section reviews the relevant literature and highlights our contribution. Section 2 describes the data and our primary econometric model. Section 2.3 outlines the econometric analysis, with empirical results presented in Section 3. We interpret these results within the context of our structural model in Section 4. 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 Empirical Methods

2.1 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 $CD_{t+1} > 0$.[6] We drop 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.

In turn, we restrict each card to having only one delinquency period, either the one in response to which it is eventually charged-off, or, if it is not eventually charged off, to the one with the most cycles delinquent. If there is a conflict we take the earlier delinquency period. Our final sample contains 7,054 borrowers who hold 16,133 cards, 6,793 of which are eventually charged-off.

2.2 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* − *Repayment*) is £-10.88.

[6] 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.

The average credit limit is £4,807.7, and the average APR is 22.3%. *Utilization* ($\frac{Closing\ Balance}{Credit\ Limit}$) is on average 74.7%, which implies a £1,231.3 of *Credit Available* on each card (*Credit Limit* − *Opening Balance* − *Charges and Fees*).[7] *Net Utilization* ($\frac{Net\ Borrowing}{Credit\ Available}$) 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 average, in the whole sample, borrowers are 1.47 months delinquent. Figure 1 shows the fraction or probability that a delinquent card gets charged off depending on the number of months they are delinquent. Around 60% of cards are charged off after being delinquent for seven months and around 20% are charged off at the four months mark. Note that, this figure restricts to cards that are part of a synchronous delinquency.

In Figure 2 we display the distribution of net borrowing and repayment for cards that are part of a synchronous delinquency. We can see that around 20% to 45% of observations are zero at each delinquency cycle point whereas the rest exhibit quite some variation. It does not seem to be the case that cards are completely inactive or frozen during the synchronous delinquency spells.

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

2.3 Model Specification

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

[7] 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.

$$
\begin{aligned}
NetBorrowing_{ijt} = {} & \beta_0 CreditAvail_{ijt} + \beta_1 ChargedOff_{ij} \times CreditAvail_{ijt} \\
& + \beta_2 Pre(\text{-}3,\text{-}1)_{ijt} \times CreditAvail_{ijt} + \beta_3 Pre(\text{-}3,\text{-}1)_{ijt} \times ChargedOff_{ij} \times CreditAvail_{ijt} \\
& + \beta_4 Post(0\text{-}7)_{ijt} \times CreditAvail_{ijt} + \beta_5 Post(0\text{-}7)_{ijt} \times ChargedOff_{ij} \times CreditAvail_{ijt} \\
& + \beta_6 Post(>7)_{ijt} \times CreditAvail_{ijt} + \beta_7 Post(>7)_{ijt} \times ChargedOff_{ij} \times CreditAvail_{ijt} \\
& + SyncedDelinqs_{ij} \Big[\delta_0 CreditAvail_{ijt} + \delta_1 ChargedOff_{ij} \times CreditAvail_{ijt} \\
& \qquad + \delta_2 Pre(\text{-}3,\text{-}1)_{ijt} \times CreditAvail_{ijt} \\
& \qquad + \delta_3 Pre(\text{-}3,\text{-}1)_{ijt} \times ChargedOff_{ij} \times CreditAvail_{ijt} \\
& \qquad + \delta_4 Post(0\text{-}7)_{ijt} \times CreditAvail_{ijt} \\
& \qquad + \delta_5 Post(0\text{-}7)_{ijt} \times ChargedOff_{ij} \times CreditAvail_{ijt} \\
& \qquad + \delta_6 Post(>7)_{ijt} \times CreditAvail_{ijt} \\
& \qquad + \delta_7 Post(>7)_{ijt} \times ChargedOff_{ij} \times CreditAvail_{ijt} \Big] \\
& + \boldsymbol{\zeta}^{\top} \mathbf{X}_{ijt} + \alpha_{it} + \varepsilon_{ijt}. \qquad (1)
\end{aligned}
$$

$NetBorrowing_{ijt}$ is discretionary borrowing (i.e., borrowing excluding fees) minus repayment in month t on card j. $CreditAvail_{ijt}$ 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. $ChargedOff_{ij}$ is an indicator that equals 1 if card j is ultimately charged off (after entering its delinquency, note that, we restrict each card to having only one delinquency period) during the sample (i.e., a DD card). $ChargedOff_{ij} = 0$ for cards that are delinquent only (DO cards).

Denote by τ_{ij} the first month in which card j held by borrower i becomes delinquent (as mentioned, we require two consecutive missed minimum payments). The time indicators

are as follows: $\textit{Pre(-3,-1)}_{ijt} = 1$ for the three months preceding delinquency, i.e., $t \in \{\tau_{ij} - 3, \tau_{ij} - 2, \tau_{ij} - 1\}$; $\textit{Post(0-7)}_{ijt} = 1$ for months $t \in \{\tau_{ij}, \tau_{ij} + 1, \ldots, \tau_{ij} + 7\}$ (0–7 months after delinquency); $\textit{Post(>7)}_{ijtjt} = 1$ for $t > \tau_{ij} + 7$; months $t \leq \tau_{ij} - 4$ form the omitted category.

The indicator $\textit{SyncedDelinqs}_{ij}$ 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 are ultimately charged off as part of that delinquency spell. We also require that borrower i has *no prior charge-off* on any card before τ_{ij}. If these conditions are met, then $\textit{SyncedDelinqs}_{ij} = 1$.

$\mathbf{X}_{ijt}$ 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 synchronous delinquent restriction embodied in $\textit{SyncedDelinqs}_{ij} = 1$ 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 $\textit{SyncedDelinqs}_{ij} = 1$ 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. (1), any unobserved liquidity, income, or information shock that triggered the simultaneous missed payments is absorbed, so within these synchronous delinquent 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-synchronous delinquencies alongside synchronous ones preserves statistical power. Synchronous 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 synchronous delinquent indicator rather than conditioning on it allows us to difference synchronous against non-synchronous 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 1 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 $ChargedOff_{ij}$ (DD vs. DO cards), and (iii) differentially for synchronous delinquent cards $SyncedDelinqs_{ij} = 1$ through the δ coefficients. Because the synchronous delinquent 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.

$$\Theta_{co}^{\text{post}}(A) \;=\; \frac{\partial NetBorrowing_{ijt}}{\partial CreditAvail_{ijt}}\Big| Post(0\text{-}7)_{ijt} = 1,\; ChargedOff_{ij} = co,\; SyncedDelinqs_{ij} = A,$$

denote the post-delinquency (0-6 months) credit sensitivity for cards with charge-off status $co \in \{0, 1\}$ (where $co = 1$ denotes DD and $co = 0$ denotes DO) and synchronous delinquent status $A \in \{0, 1\}$.

From Eq. (1),

$$\Theta_{DO}^{\text{post}}(A=1) = (\beta_0 + \beta_4) + (\delta_0 + \delta_4), \tag{2}$$

$$\Theta_{DD}^{\text{post}}(A=1) = (\beta_0 + \beta_1 + \beta_4 + \beta_5) + (\delta_0 + \delta_1 + \delta_4 + \delta_5). \tag{3}$$

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

$$\begin{aligned}\Delta\Theta_{\text{DD–DO}}^{\text{post}}(A=1) &= \Theta_{\text{DD}}^{\text{post}}(A=1) - \Theta_{\text{DO}}^{\text{post}}(A=1) \\ &= (\beta_1 + \beta_5) + (\delta_1 + \delta_5). \end{aligned} \tag{4}$$

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

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

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

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

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 $\widehat{\Theta}_{DO}^{\text{post}}(A=1)$, $\widehat{\Theta}_{DD}^{\text{post}}(A=1)$, their difference

$\Delta\Theta^{\text{post}}_{\text{DD–DO}}(A=1)$, and F-tests of both H_0^{strong} and H_0^{weak}.

3 Results

3.1 Baseline Analysis

Table 2 shows the results when estimating Equation 1. We start the analysis by estimating the model in hypothetically generated data where individuals max-out DD cards in synchronous delinquencies ($SyncedDelinqs_{ij} = 1$) when delinquency starts, whereas they do no borrow on the corresponding DO cards. To do this, we set $NetBorrowing_{ijt}$ equal to $CreditAvail_{ijt}$ in the first month of delinquency for synchronous delinquent DD cards, and then set both these variables to zero thereafter. We set $NetBorrowing_{ijt}$ equal to zero post delinquency for synchronous delinquent DO cards. The results of our model with the hypothetical data are presented in Column (1), and with the actual data are in Column (2).

The coefficient β_0 is the baseline sensitivity of $NetBorrowing_{ijt}$ to $CreditAvail_{ijt}$ for the reference category (in the period ending 3 months prior to the start of delinquency). The coefficients β_1 to δ_5 represent the interactions between $CreditAvail_{ijt}$ and the other variables ($Post(0\text{-}7)_{ijt}$, $SyncedDelinqs_{ij}$, $ChargedOff_{ij}$) in the model and reflect the changes in the slope in relation to the baseline category. The results from the strong and weak opportunistic borrowing tests, and their corresponding p-values, are shown in the bottom rows of Table 2.

In the hypothetical scenario in Column (1), the strong opportunistic borrowing test shows that $\Theta^{\text{post}}_{\text{DD}}(A=1)$ equals one. The weak opportunistic borrowing test shows that the difference in slopes after delinquency for DD vs DO synchronously delinquent cards ($\Delta\Theta^{\text{post}}_{\text{DD–DO}}(A=1)$) is positive and equal to one. These results provide a useful benchmark when analyzing the actual data in Column (2).

In Column (2) the baseline coefficient on $CreditAvail_{ijt}$ (β_0) is equal to 0.054 and is highly significant, showing that in the reference category one additional pound of credit available leads to an average increase in $NetBorrowing_{ijt}$ of 5.4 pence.[8] This sensitivity drops after delinquency starts, as shown by the coefficient β_4, especially for DD cards (β_5). There is a further decline to this sensitivity after delinquency for cards that are part of synchronous delinquency episodes (δ_4). Overall, the individual coefficients show a general decrease in the sensitivity of $NetBorrowing_{ijt}$ to $CreditAvail_{ijt}$ in the first seven months of delinquency for both DD and DO cards.

The strong opportunistic borrowing test in Column (2) shows that the actual $\Theta^{\text{post}}_{\text{DD}}(A=1)$ in the data equals 0.007. The hypothesis that it is equal to 1, as implied by maxing-out, is comfortably rejected. The estimate from the weak opportunistic borrowing test ($\Delta\Theta^{\text{post}}_{\text{DD–DO}}(A=1)$) is negative ($-0.003$) and statistically insignificant (p-value=0.682), indicating that there is no difference in borrowers' propensity to utilize credit after delinquency for synchronously delinquent DD vs DO cards.

In Figure 3 we conduct the dynamic versions of the strong and weak opportunistic borrowing tests using both the hypothetical (maxed-out) and actual data in each month around the start of delinquency.

The top two panels show what maxing-out looks like in the hypothetical data. There is a strong spike in the sensitivity of $NetBorrowing_{ijt}$ to $CreditAvail_{ijt}$ for DD cards in the first month of delinquency ($t=0$), and the coefficients are zero thereafter (Panel A). The DD-DO slope gap shows a similar spike in the first month of delinquency (Panel B). However, the actual data (Panels C and D) tell a completely different story, where the sensitivity of $NetBorrowing_{ijt}$ to $CreditAvail_{ijt}$ for DD cards when $SyncedDelinqs_{ij}=1$ (Panel C), or the DD-DO slope gap (Panel D) are tightly estimated at zero when $Post(0\text{-}7)_{ijt}=1$.

[8] The pre-delinquency coefficients are the same in Columns (1) and (2) since, for that part of the sample, nothing has changed.

Overall, two key findings emerge from the baseline analysis: First, there is no difference in borrowers propensity to use credit after delinquency on DD vs DO cards. Second, there is a general drop in their propensity to utilize credit on all types of cards. Collectively, these findings strongly reject the opportunistic borrowing hypothesis.

3.1.1 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 (IG)* to 1 if the utilization, revolving balance, minimum payment or APR of the specific card in month t is above the median for that specific borrower in that month. We interact IG with all the variables when estimating Equation 1.

The results are shown in Table 3. We present the coefficients that, when added, indicate the difference in the weak-form opportunistic borrowing test (i.e., the difference in the DD-DO slope gap) across IG groups when $SyncedDelinqs_{ij} = 1$. A sum that is significantly different from zero indicates a change in the weak opportunistic borrowing test across IG groups.

Column (1)-(4) show that there is no difference in the DD-DO slope gap for $SyncedDelinqs_{ij} = 1$ across the level of card indebtedness.

In Column (5), IG is defined based on the time that a card is held. It is possible that borrowers are more likely to opportunistically borrow on cards that are held for a short period of time, due to a shorter relationship with the lender. However, we don't find any evidence in support of this conjecture.

In Column (6), we define the IG group based on whether the borrower has experienced a

charged-off episode before, in another card. It is possible that borrowers with prior experience of the default process act more strategically. However, again, we find no difference in the DD-DO slope gap for $SyncedDelinqs_{ij} = 1$.

Overall, the results in this section do not reveal any cross-sectional heterogeneity in the propensity of borrowers to utilize credit on DD vs DO cards.

3.1.2 Stacked Regression Design

We also estimate a stacked version of the model (Equation 1), 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 defaults) using only clean controls, i.e., individuals that did not default over the sample period. The results are very similar and can be found in Table 4. Note that, even in the baseline specification of synchronous delinquencies, we restrict to borrowers that were charged off for the first time.

3.1.3 Stacked Regression Design with Poisson Pseudo-Likelihood Specification

In the previous specifications, we used net borrowing in absolute £values as the outcome variable which includes zeros. To make sure that our results are not driven by the presence of zeros in the outcome variable, we employ a stacked design with a Poisson pseudo-likelihood specification following the recommendation in Cohn et al. [2022]. We cannot use net borrowing here, as the variable contains negative values when repayment exceeds spending on the card, therefore, we use discretionary spending, excluding charges and fees, and repayment as outcome variables separately. We can see in Table 5 that coefficients on all interaction terms are tightly estimated zeros. Note that, we would expect that the PPML specification

corrects a bias away from zero, so these results are in line with our priors. This specification also addresses the concern that our previous null results were driven by inactive or frozen cards, as the specification restricts to cards on which there is activity (non-zero values).

3.2 Credit Card Outcomes around Delinquency

In this section we analyze various credit card outcomes around delinquency events for DD and DO cards, examining how several credit card variables change according to the indicators $Post(0\text{-}7)_{ijt}$, $ChargedOff_{ij}$ and $SyncedDelinqs_{ij}$.

The results are shown in Table 6. In Column (1) the dependent variable is *Discretionary Spending* on card j in month t. The only significant coefficient in the model is the one on $Post(0\text{-}7)_{ijt}$ indicating less borrowing (by roughly £54) on both DD and DO cards after the start of delinquency.

From Column (2), we see an increase in *Charges and Fees* after delinquency, but a decline if $SyncedDelinqs_{ij}$ and $ChargedOff_{ij}$ are equal to 1.

Column (3) shows a reduction in *Repayment* (by roughly £29) when $Post(0\text{-}7)_{ijt} = 1$, especially if the card is DD (an additional reduction of £31.7). This result aligns with the idea that these are distressed borrowers, with a reduced capacity to repay their debt due to a negative income shock.

Columns (4), (5) and (6) shows results when the dependent variable is *Net Borrowing*, *Utilization* and *Net Utilization*. The coefficient on $Post(0\text{-}7)_{ijt} \times ChargedOff_{ij}$ is positive in all cases, indicating more borrowing for DD vs DO cards after delinquency starts. However, in all cases, this increase is completely offset when $SyncedDelinqs_{ij} = 1$, as shown by the coefficient on $SyncedDelinqs_{ij} \times Post(0\text{-}7)_{ijt} \times ChargedOff_{ij}$. These results highlight that importance of conditioning on $SyncedDelinqs_{ij}$ when drawing inferences on opportunistic borrowing. When

delinquencies are not synchronous (and hence possibly driven by different income shocks) we observe a higher propensity to borrow on DD vs DO cards when $Post(0\text{-}7)_{ijt} = 1$. However, when condition on the same income shock via $SyncedDelinqs_{ij} = 1$, we actually see that there is no difference in borrowing between DD vs DO cards.

In Column (7) the dependent variable is *Credit Limit*, showing an increase for DD cards relative to DO cards that enter delinquency asynchronously, which is offset for synchronous cards. The dependent variable in Column (8) is *APR*, which does not how any significant variation according to the indicators $Post(0\text{-}7)_{ijt}$, $ChargedOff_{ij}$ and $SyncedDelinqs_{ij}$.

Figure 4 shows the predicted margins for *Net Borrowing* (Panel A), *Net Utilization* (Panel B), *Repaynent* (Panel C), and *Utilization* (Panel D) for DO and DD cards when $SyncedDelinqs_{ij} = 1$. From Panel (A), we see that *Net Borrowing* is negative after the start of delinquency for both DD and DO cards, in line with our findings in Table 2. Same results are shown in Panel (B) for *Net Utilization*. In Panel (C), *Repayment*, we see that repayment is positive for both DD and DO cards. Finally in Panel (D), *Utilization*, we observe an increase for both DD and DO cards in the months leading to delinquency, a leveling off in the first 4 delinquent months, and a decline thereafter.

Overall, two key findings emerge from the margin plots: First, after delinquency, there is no difference in *Net Borrowing*, *Repayment* or *Utilization* between for DD and DO cards with synchronous delinquencies, which goes against the opportunistic borrowing hypothesis. Secondly, we find negative *Net Borrowing* and positive *Repayment* after delinquency, a finding which seems to contradict the predictions from standard consumption-smoothing models, in which borrowing should increase to smooth consumption after a negative income shock.

3.3 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? Borrowers are only able to borrow opportunistically, if they can, at least to some extent, predict which cards will be charged offs. 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, we 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%. Therefore, individuals are likely to be able to predict which cards are charged off as well.

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 are 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.

Figure 5 plots the dynamic responses of the charge-off rate, credit limits, and APRs of the other cards around default events (i.e., the remaining cards of a borrower, after defaulting on a separate card). From the left Panels (A), (C) and (E) we can see that defaulting on

one card significantly increases the charge-off rate, by about 10%, which indicates that the borrower is placed in a riskier risk band. Credit limits are also lower, by an average of £700, which indicates that borrowing becomes more restricted. *APRs* (Panel (E)) show a small drop of about 1 percentage point. This is a bit surprising but can be explained by the fact that, in the UK, regulations prevent credit card providers to increase APRs for more risky borrowers [Matcham, 2025].

The Panels on the right do the same estimation whilst including the interaction between being charged off and the amount that was charged off (coded in ten bins). The coefficient on this variable is an estimate of the marginal default costs, for an extra pound defaulted. As shown in Panels (B), (D) and (F) the interaction coefficients with amount charged off are indistinguishably close to zero.

These findings show that, whilst defaulting on a card is very costly, the amount defaulted does not seem to be very consequential. This suggests that the economic incentives deterring opportunistic borrowing do not seem to be strong.

3.4 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

[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.

debt collector can chase a defaulter for a debt in the UK is governed by the Limitation Act (1980). Most unsecured debts, such as personal loans, credit cards, and utility bills, have a limitation period of six years. Once the limitation period has expired, it means the debt is statute barred and can no longer be legally enforced in court.[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 won't be able to re-register it, even if money is still owed.[13]

4 Structural Analysis

In this section, we present a parsimonious model to study the credit utilization of a delinquent borrower facing default risk. The model setup closely aligns with the empirical design in Section 2.3. Agents hold several credit cards, each of which may be either delinquent or current, and face liquidity shocks common to all cards. Default risk is card-specific, and agents strategically decide which cards, if any, to use to finance consumption.

We consider a single agent holding $N \geq 2$ credit cards, where cards are indexed by j.[14] Each card has credit limit L_j and interest rate r_j. Let g_{jt} denote the delinquency status of card j; at any point t, each card is either delinquent ($g_{jt} = \mathcal{D}$) or current ($g_{jt} = \mathcal{C}$). A card is current if for each $s \leq t$, the agent has made at least the required minimum payment $m_j B_{js}$, where $m_j = r_j + \pi_j < 1$. In words, to keep a card current, the agent must continually make their minimum payment, where the minimum payment is given by accrued interest $r_j B_{jt}$ plus an exogenous fraction $\pi_j B_{jt}$ of the outstanding balance.

While in delinquency, agents skip the minimum payment. Let d_j denote the length of time in

[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.

[14] We temporarily omit agent indices for notational brevity. When discussing estimation in Section 4.2, we introduce indices (i) corresponding to each agent in the data.

delinquency for card j, where $d_j = 0$ for $g_{jt} = \mathcal{C}$. Given d_j, let $H_{jt} = \int_0^{d_j} m_j B_{js} ds$ denote the cumulative level of missed minimum payments. Further, while $g_{jt} = \mathcal{D}$, card j accumulates flow late fees ℓ_j, which we assume are constant over time for simplicity.[15] Let $F_{jt} = d_j \ell_j$ denote the total level of accumulated late fees. To "cure" their account (i.e. transition from delinquent to current), the agent must pay $F_{jt} + H_{jt}$. Importantly, while $g_{jt} = \mathcal{D}$, card j faces a risk of default. Default shocks for card j arrive at rate $\lambda(d_j)$. We assume that $\lambda'(d_j) > 0$, so the risk of default grows with time in delinquency. If card j defaults, the borrower incurs card-specific default penalty $\kappa + \alpha B_{jt}$, where κ is a baseline cost of default and α measures the sensitivity of default costs to the defaulted amount. We henceforth refer to α as the marginal cost of default.

Letting c_t denote time-t consumption, agents have flow utility $u(c_t)$ where $u'(c_t) > 0$ and $u''(c_t) < 0$. At each point in time, agents makes a consumption decision subject to the budget constraint:

$$c_t \leq W_t + \sum_j s_{jt} \tag{5}$$

where W_t denotes the agent's liquid wealth and s_{jt} denotes spending on card j where $0 \leq s_{jt} \leq L_j - B_{jt}$. In words, (5) states that agents have the option to finance consumption either out of their liquid wealth or through additional credit card spending, where spending on card j is bounded above by the remaining credit $L_j - B_{jt}$. The agent's liquid wealth has the law of motion:

$$\dot{W}_t = y_t - c_t + \sum_j s_{jt} - \sum_{j \in \mathcal{C}} m_j B_{jt} - \sum_{j \in \mathcal{D}} x_{jt} \tag{6}$$

y_t denotes the agent's time-t income, $\sum_{j \in \mathcal{C}} m_j B_{jt}$ denotes minimum payments made on current cards, and $\sum_{j \in \mathcal{D}} x_{jt}$ denotes arrears paid on delinquent cards. Credit balances evolve

[15] In the UK, late fees typically amount to £12 per delinquent cycle.

as follows:[16]

$$\dot{B}_{jt} = \begin{cases} -\pi_j B_{jt} + s_{jt} & j \in \mathcal{C} \\ r_j B_{jt} + s_{jt} & j \in \mathcal{D} \end{cases} \tag{7}$$

Let B_t be a vector whose j^{th} element is B_{jt}, and define F_t, H_t, and d_t analogously. The state is given by (W, X) where $X = (B, F, H, d)$, i.e., the state variables are the beginning-of-period balances on all cards, the accumulated late fees, the accumulated missed minimum payments, and the cycles delinquent the card (zero for current cards). The agent's value function is given by:

$$U(W, X) = \max_{c, \mathbf{s}, \mathbf{x}} \mathbb{E}\left[\int_0^\infty e^{-\rho t} u(c_t) dt - \sum_j \mathbf{1}[\tau_j < \infty] e^{-\rho \tau_j} (\kappa_j + \alpha_j B_{j\tau_j}) \right] \tag{8}$$

where τ_j is the time of default for card j and $\tau_j < \infty$ denotes that card j is eventually charged off (i.e. defaults). Thus, agents choose a path of consumption c, a vector of spending policies $\mathbf{s}$, and a vector of repayment policies $\mathbf{x}$ to maximize the discounted net present value of consumption net of any costs associated with future default.

To solve the model, we first reformulate (8) as the solution to a partial differential equation. To this end, we first define the cure operator $\mathcal{K}_i$ as:

$$\mathcal{K}_j : (W, B_j, H_j, F_j, d_j) \to (W - H_j - F_j, B_j - H_j, 0, 0, 0) \tag{9}$$

In words, by curing card j, the agent reduces their liquid wealth by $H_{jt} + F_{jt}$. Further, the balance on card j falls by H_j, and the (H_j, F_j, d_j) balances are reset to $(0, 0, 0)$. Define the gain from curing card j as:

$$G_j(W, X) \equiv U(\mathcal{K}_j(W, X)) - U(W, X) \tag{10}$$

[16] While current, $\dot{B}_{jt} = r_j B_{jt} + s_{jt} - m_j B_{jt} = -\pi_j B_{jt} + s_{jt}$.

If $\max_{j\in\mathcal{D}} G_j(W,X) \geq 0$, the agent cures account j at instant t. Otherwise, if $\max_{j\in\mathcal{D}} G_j(W,X) < 0$, the agent refrains from curing any card. While in this "inaction" region, cure payments x_{jt} are fixed at zero and the agent makes consumption c and spending $\mathbf{s}$ decisions. Let $(c,\mathbf{s})$ denote an arbitrary set of consumption and spending policies. Under $(c,\mathbf{s})$, agent value satisfies:

$$V(W,X;c,\mathbf{s}) = u(c) + U_W\left(y - c + \sum_j s_j - \sum_{j\in\mathcal{C}} m_j B_j\right) + \sum_{j\in\mathcal{D}}\left(U_{B_j}(r_j B_j + s_j) + U_{d_j} + U_{H_j} m_j B_j + U_{F_j}\ell_j\right)$$
$$+ \sum_{j\in\mathcal{C}} U_{B_j}(s_j - \pi_j B_j) + \sum_{j\in\mathcal{D}} \lambda_j(d_j)(-\kappa_j - \alpha_j B_j + U(W,\mathcal{R}_j X) - U(W,X)) \tag{11}$$

The value function (8) then satisfies:

$$\max\{\rho U - \max_{c,\mathbf{s}}\ V(W,X;c,\mathbf{s}), \max_{j\in\mathcal{D}}\ G_j(W,X)\} = 0 \tag{12}$$

The first argument in the max operator denotes the agent's value in the inaction region. Here, no accounts are cured, and the agent spends and consumes optimally. The second argument denotes the agent's value in the action region. Here, the agent selects the card yielding the highest cure gain, pays the associated arrears x_{jt}, and card j is make current thereafter.

4.1 Optimal Credit Utilization

Proposition 1. *Let $g_{jt} \in \{\mathcal{C},\mathcal{D}\}$ denote the delinquency status of card j. The optimal spending policy satisfies:*

$$s_{jt} = \begin{cases} L_j - B_{jt} & u'(c_t) > T_{jt}^{g_{jt}} \\ 0 & u'(c_t) < T_{jt}^{g_{jt}} \end{cases} \tag{13}$$

where $T_{jt}^{g_{jt}}$ *is defined by:*

$$T_{jt}^{\mathcal{C}} = U_W \frac{r_j + \pi_j}{\rho + \pi_j} \tag{14}$$

$$T_{jt}^{\mathcal{D}} = \alpha \frac{\lambda(d_j)}{\rho - r_j + \lambda(d_j)} \tag{15}$$

Proof. See Appendix A.1. □

Optimal credit card spending follows a simple threshold rule in which the marginal utility of consumption $u'(c_t)$ is weighed against a card-specific value $T_{jt}^{g_{jt}}$. Equation (14) defines the relevant threshold for current cards. Spending on current cards commits agents to future minimum payments. The threshold $T_{jt}^{\mathcal{C}}$ measures the future loss of wealth stemming from these minimum payments, converted into present value terms.[17] The spending rule thus implies, for current cards, that agents utilize all available credit if the marginal value of consumption exceeds future wealth losses stemming from minimum payments.

The delinquent threshold $T_{jt}^{\mathcal{D}}$ similarly measures the net present value of future costs associated with spending on delinquent cards. While delinquent, increasing the balance B_{jt} by one unit raises the potential default penalty by α. Multiplying α by $\lambda(d_j)$ gives the expected marginal cost of default over a unit time interval, and scaling by $\rho - r_j + \lambda(d_j)$ converts to present value terms. So, the spending rule (13) simply states that if the agent's marginal value of consumption surpasses the expected penalty associated with an extra defaulted pound, maxing out is the best the agent can do.

[17] By equation (6), spending £1 on card j decreases the drift of W_t by $m_j = r_j + \pi_j$. Multiplying m_j by U_W yields the instantaneous loss in value emanating from this decrease in wealth. Noting that absent further spending, credit balances on current cards decay at rate π_j (Equation (7)), dividing $m_j U_W$ by $\rho + \pi_j$ converts to present value terms.

4.2 Estimation & Identification

We next analyze differences in borrowing between DD and DO cards through the lens of the model formulated above. Letting $\Delta B_{ijt} = B_{ijt+\Delta} - B_{ijt}$ denote net borrowing for agent i over a short time interval $[t, t+\Delta]$, we can define the theoretical counterparts to the slopes defined in Section 2.3:

$$\Theta_{DO} = \mathbb{E}\left[\frac{\partial \Delta B_{ijt}}{\partial A_{ijt}} \mid ij \in DO\right] \tag{16}$$

$$\Theta_{DD} = \mathbb{E}\left[\frac{\partial \Delta B_{ijt}}{\partial A_{ijt}} \mid ij \in DD\right] \tag{17}$$

where $A_{ijt} = L_{ij} - B_{ijt}$ denotes credit available on card j at time t. The spending rule (13) implies:

$$\frac{\partial \Delta B_{ijt}}{\partial A_{ijt}} = \begin{cases} 1 & u'(c_{it}) > T_{ij}^{g_{ijt}} \\ 0 & u'(c_{it}) < T_{ij}^{g_{ijt}} \end{cases} \tag{18}$$

In words, if agents' marginal utility of consumption $u'(c_{it})$ is sufficiently large, agents draw down all available credit; hence, $\frac{\partial \Delta B_{ijt}}{\partial A_{ijt}} = 1$. Otherwise, spending is zero, so $\frac{\partial \Delta B_{ijt}}{\partial A_{ijt}} = 0$. For brevity, we define $\mu_{it} \equiv u'(c_{it})$ as the time-varying, borrower-specific marginal utility process which, importantly, is unobserved to the econometrician. Using Equation (18), we can express the slopes (16) and (17) as:

$$\Theta_{DO} = Pr\left(\mu_{it} > T_{ij}^{g_{ijt}} \mid j \in DO\right) = \mathbb{E}[S_\mu(T_{ij}^{g_{ijt}}) \mid j \in DO] \tag{19}$$

$$\Theta_{DD} = Pr\left(\mu_{it} > T_{ij}^{g_{ijt}} \mid j \in DD\right) = \mathbb{E}[S_\mu(T_{ij}^{g_{ijt}}) \mid j \in DD] \tag{20}$$

where $S_\mu(x) = 1 - Pr(\mu_{it} < x)$ is the survival function of μ_{it}. We make the parsimonious distributional assumption:

$$S_{\mu_{it}}(x) = exp(-x^k) \tag{21}$$

under the distributional assumption (21), the marginal utility process μ_t follows a Weibull distribution with shape parameter k and scale parameter normalized to 1. Define the event-time variable $\tau_{ijt} \in \{-3, \ldots, 6\}$ which tracks the time since card ij first entered delinquency. For example, a value of -2 indicates that card ij will enter delinquency in two periods, 0 if the card has just entered delinquency, and 2 if the card entered delinquency two periods ago. We estimate the model by matching for each $\tau_{ijt} \in \{-3, \ldots, 6\}$ the model implied slopes:

$$\Theta^{\tau}_{DO} = \mathbb{E}\left[exp\Big(-(T_{ij}^{g_{ijt}})^k\Big) \mid \tau_{ijt} = \tau, ij \in DO\right] \tag{22}$$

$$\Theta^{\tau}_{DD} = \mathbb{E}\left[exp\Big(-(T_{ij}^{g_{ijt}})^k\Big) \mid \tau_{ijt} = \tau, ij \in DO\right] \tag{23}$$

against their empirical counterparts implied by the estimates of Equation (1), yielding a total of 20 target moments. Noting that $\tau_{ijt} < 0$ implies that card ij is current in period t, while $\tau_{ijt} \geq 0$ implies that card ij is delinquent in period t, we have that:

$$T_{ij}^{g_{ijt}} = T_{ij}^{\mathcal{D}} = \alpha \frac{\lambda(d_{ijt})}{\rho - r_{ij} + \lambda(d_{ijt})} \quad \text{if} \quad \tau_{ijt} \geq 0 \tag{24}$$

$$T_{ij}^{g_{ijt}} = T_{ij}^{\mathcal{C}} = U_W \frac{r_{ij} + \pi}{\rho + \pi} \quad \text{if} \quad \tau_{ijt} < 0 \tag{25}$$

Recalling the optimal spending rule (Equation (13)), agents face two distinct borrowing regimes depending on the delinquency status of the relevant card. While delinquent ($\tau_{ijt} \geq 0$) agents spend on card j only if the marginal utility process μ_{it} exceeds the threshold $T_{ij}^{\mathcal{D}}$. The value of this threshold is governed by the marginal cost of default α, the arrival rate of default shocks $\lambda(d_{ijt})$, the APR r_{ij}, and the subjective discount rate ρ. We estimate the arrival of default shocks $\lambda(d_{ijt})$ directly from the data and use the consequent estimates $\hat{\lambda}(d_{ijt})$ as an input to the structural estimation routine. r_{ij} is observed in the data, leaving α and ρ as parameters to estimate.

While card j is current ($\tau_{ijt} < 0$), agent i spends on card j only if μ_{it} surpasses $T_{ij}^{\mathcal{C}}$, whose value depends on the APR r_{ij}, minimum payment rate π, discount rate ρ, and shadow value

of wealth U_W. We fix the value of π to .03 in estimation and treat U_W as a parameter to estimate. Of course, the shadow value of wealth U_W is truly a complex function of agent i's state. Our estimate of U_W should then be interpreted as the slope of agents' value function with respect to W averaged across the state variables defined in the decision problem above.

We estimate the model via GMM using the empirical slopes Θ^{τ}_{DO} and $\Theta^{\tau}_{DD,}$ for $\tau \in \{-3, \ldots, 6\}$ as target moments. Let $\omega = (\alpha, U_W, \rho)$ denote an arbitrary vector of structural parameters.[18] Let $\widehat{\Theta}$ be the the 20×1 stacked vector of empirical moments and let Θ^{model} be a similarly-defined vector of model-implied moments defined in Equations (22) and (23). Finally, let W denote the inverse of the variance/covariance matrix of $\widehat{\Theta}$. Then, the estimates $\hat{\omega}$ minimize the quadratic form:

$$\hat{\omega} = \arg\min_{\omega} \left(\widehat{\Theta} - \Theta^{model}(\omega)\right)^{\top} W \left(\widehat{\Theta} - \Theta^{model}(\omega)\right) \tag{26}$$

The estimation procedure proceeds as follows. First, we obtain a reduced-form estimate of the default rate $\hat{\lambda}(d)$. Given $\hat{\lambda}(d)$ and data $\{d, \tau, r\}$, we minimize (26) using the Simulated Annealing algorithm. On each iteration, $\Theta^{model}(\omega)$ is computed under a candidate ω and the objective function is evaluated. This repeats until the algorithm halts. A summary of model fit is provided in Figure 6. Panel (a) plots the model-implied estimates of Θ^{τ}_{DD} against their empirical counterparts, where error bars correspond to 95% confidence intervals; Panel (b) does the same for Θ^{τ}_{DO}.

4.3 Structural Estimates

Parameter estimates are reported in Table 9. The value of α (8.07), measuring borrowers' perceived cost of defaulting on an additional pound, is estimated to be quite high. Scaling α by the estimated shadow value of wealth, U_W (3.72), allows for a per-pound interpretation:

[18] We fix the value of the distributional parameter $k = 1$ for now.

delinquent borrowers behave as if defaulting on £1 costs $\alpha/U_W \approx$ £2.17 in consumption-equivalent units. This estimate is remarkably high given the institutional reality of UK credit markets. Upon default in the UK, the relevant credit-file event is the default marker itself, a binary indicator which does not scale proportionally with the defaulted amount.[19] In other words, what matters in the eyes of credit issuers is whether or not one has defaulted, not the amount defaulted on. Additionally, post charge-off recovery rates on unsecured credit card debt are quite low [Fedaseyeu, 2020, Matcham, 2025]. It is thus the case that defaulting on, for example, £10K and £20K yield essentially the same penalty as (1) penalties regarding future credit access and pricing do not scale with defaulted balances and (2) recovery rates are negligible in either case. Finally, in our own data, the amount defaulted does not seem to affect the charge-off rate, credit limits, and APRs, as we discuss in Subsection 3.3

Squaring our estimate of α against these institutional details, our results suggest that non-pecuniary factors must be at play when explaining agents' hesitation to borrow opportunistically. Put differently, if agents' subjective beliefs about the cost of default accurately reflected the institutional environment, we should expect an estimate of α which is close to zero. As our estimate is positive and statistically significant, our results point towards agents having misspecified beliefs about the costs of default. To illustrate the effects of such belief misspecification, we conduct a simple counterfactual experiment in which we set the marginal default cost α to zero. This counterfactual setting reflects a "rational" benchmark in which agents are fully aware that default penalties are discrete, and do not scale with the defaulted balance. We plot the results of this counterfactual exercise in Figure 7. In the Figure, we plot the baseline model-implied slopes, Θ^{τ}_{DD} (black dots), against counterfactual slopes in which $\alpha = 0$ (red dots). In the counterfactual, each of the post-delinquency slopes are near-one, indicating that nearly all agents rationally utilize all available credit on their eventually-charged-off (DD) cards.

[19] See for example: https://www.experian.co.uk/consumer/guides/defaults.html.

Recall that the card-specific thresholds T_{ij}^g defined in Equation (13) measure agent i's cost of borrowing on card j. To further analyze agents' observed borrowing behavior, we compute the borrowing costs T_{ij}^g for each card in the data given the estimates in Table 9; we plot these distributions in Figure 8. Panel (a) plots the empirical CDF of $T_{ij}^{\mathcal{C}}$ against that of $T_{ij}^{\mathcal{D}}$, thereby comparing agents' subjective cost of borrowing on current cards relative to delinquent cards. The distribution of $T_{ij}^{\mathcal{D}}$ lies far to the right of the distribution of $T_{ij}^{\mathcal{C}}$, indicating that in the eyes of borrowers, spending on delinquent cards is significantly more costly than spending on current cards. For reference, the average value of $T_{ij}^{\mathcal{D}}$ (6.57) is over twice that of $T_{ij}^{\mathcal{C}}$ (3.11), suggesting that agents' perceived cost of borrowing on a delinquent card is, on average, more than double that of borrowing on a current card. Thus, for agents holding multiple credit cards, some of which are delinquent and some of which are current, borrowing on a current card is virtually always preferable to borrowing on a delinquent card.

Panel (b) of Figure 8 restricts attention to delinquent cards and compares the distributions of $T_{ij}^{\mathcal{D}}$ for DD and DO cards. Letting F^x denote the distribution of $T_{ij}^{\mathcal{D}}$ conditional on $x \in \{DD, DO\}$, the Figure illustrates that $F^{DD} \leq F^{DO}$, so the distribution of DD thresholds first-order stochastically dominates that of the DO threshold distribution. Under this condition, we have the following result:

Proposition 2. *Assume that $F^{DD} \leq F^{DO}$. Then:*

$$\Theta_{DD}^{\mathcal{D}} \leq \Theta_{DO}^{\mathcal{D}} \tag{27}$$

where $\Theta_{DO}^{\mathcal{D}}$ and $\Theta_{DD}^{\mathcal{D}}$ are respectively defined by Equations (16) and (17).

Proof. See Appendix A.1. □

Proposition 2 shows that the reduced-form results established in Section 3 are guaranteed to hold if F^{DD} first-order stochastically dominates F^{DO}, meaning that for agents holding

multiple credit cards, all of which are delinquent, borrowing on a DO card is (on average) weakly preferable to borrowing on a DD card. To highlight what generates differences in borrowing costs for DD and DO cards, it is helpful to note the following identity:

$$\mathbb{E}[T_{ij}^{\mathcal{D}} \mid j \in DD] - \mathbb{E}[T_{ij}^{\mathcal{D}} \mid j \in DO] = \alpha\Big(\mathbb{E}[q_{ijt} \mid j \in DD] - \mathbb{E}[q_{ijt} \mid j \in DO]\Big) \tag{28}$$

$$q_{ijt} = \frac{\lambda(d_{ijt})}{\rho - r_{ij} + \lambda(d_{ijt})} \tag{29}$$

When explaining average differences in borrowing costs between DD and DO cards, where costs are measured via the thresholds $T_{ij}^{\mathcal{D}}$, the parameter $\alpha \geq 0$ simply acts as a scaling factor which cannot flip the sign of Equation (28). Thus, α alone cannot explain why the ordering $F^{DD} \leq F^{DO}$ holds empirically. Differences in borrowing costs between the two card types are instead explained by systematic differences in the ratio q_{ijt}. Note that q_{ijt} increases in both the default rate $\lambda(d_{ijt})$ and APR r_{ij}; so, when $\alpha > 0$, borrowing on a delinquent card increases with respect to the likelihood of default (in which case the agent bears any associated penalties) and the card's interest rate (which speeds the growth of the eventually-defaulted balance).

Focusing first on the APR r_{ij}, DD cards in the estimation sample have (on average) a significantly higher interest rate than their DO counterparts. This is indicative of endogenous selection. When choosing which of their cards to cure (i.e. exit delinquency), this gap suggests that agents systematically select lower-APR cards to cure, leaving higher-APR cards in delinquency thereby increasing their chance of eventual default. In other words, cards which receive the ex-post DD classification have systematically higher interest rates and are therefore more expensive to borrow on, as a consequence of agents endogenously selecting lower-APR cards to cure first.

Regarding the default rate $\lambda(d_{ijt})$, note first that this function is estimated to be strictly increasing with respect to the duration in delinquency d_{ijt}. Further, $\lambda(d_{ijt})$ is significantly

larger for DD cards than their DO counterparts, implying that DD cards (on average) spend longer periods of time in delinquency than DO cards. This is similarly the consequence of endogeneity in the ex-post DD/DO classification. Cards which spend long periods of time in delinquency are especially likely to be eventually charged off and receive the DD classification. These high-$\lambda(d_{ijt})$ cards are relatively costly to borrow on, as increases in their balance are associated with a large increase in expected default penalties.

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.

Overall, our results suggest that the credit default decision is not binary, and is likely in-

fluenced 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						

The initial sample contains 2,190,216 borrowers, 0.95% of which experience default. 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 $CD_{t+1} > 0$. We drop cards that become charged off without going delinquent. We also remove cards that start off in the sample as delinquent. We restrict each card to having only one delinquency period, either the one in response to which it is eventually charged-off, or, if it is not eventually charged off, to the one with the most cycles delinquent. If there is a conflict we take the earlier delinquency period. Our final sample contains 7,054 borrowers who hold 16,133 cards, 6,793 of which are eventually charged off. *Net Borrowing* equals *Discretionary Spending − Repayment*. *Utilization* equals $\frac{Closing\ Balance}{Credit\ Limit}$ and *Credit Available* on each card equals *Credit Limit − Opening Balance − Charges and Fees*. *Net Utilization* equals $\frac{Net\ Borrowing}{Credit\ Available}$.

Table 2: Tests for Opportunistic Borrowing

	(1) Max-Out Hypothetical Net Borrowing	(2) Actual Net Borrowing
CreditAvail (β_0)	0.054***	0.054***
	(0.002)	(0.002)
ChargedOff × CreditAvail (β_1)	0.013***	0.013***
	(0.004)	(0.004)
Post(0-7) × CreditAvail (β_4)	-0.036***	-0.036***
	(0.002)	(0.002)
Post(0-7) × ChargedOff × CreditAvail (β_5)	-0.018***	-0.018***
	(0.004)	(0.004)
SyncedDelinqs × CreditAvail (δ_0)	0.019***	0.019***
	(0.006)	(0.006)
SyncedDelinqs × ChargedOff × CreditAvail (δ_1)	-0.012	-0.012
	(0.009)	(0.009)
SyncedDelinqs × Post(0-7) × CreditAvail (δ_4)	-0.036***	-0.028***
	(0.007)	(0.007)
SyncedDelinqs × Post(0-7) × ChargedOff × CreditAvail (δ_5)	1.016***	0.014
	(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: $\beta_0 + \beta_1 + \beta_4 + \beta_5 + \delta_0 + \delta_1 + \delta_4 + \delta_5 = 1$	1.000	0.007
Strong Opportunistic Borrowing: p-value	0.454	0.000
Weak Opportunistic Borrowing : $\beta_1 + \beta_5 + \delta_1 + \delta_5 > 0$	0.999	-0.003
Weak Opportunistic Borrowing : p-value (one-sided)	0.000	0.682

This table presents our main test results for opportunistic borrowing. We restrict the sample to borrowers who, during the sample period, have at least two cards go delinquent; for these borrowers, we keep only the delinquent cards. *CreditAvail* 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 *CreditAvail* is negative we set it to zero. *NetBorrowing* is the difference between borrowing in month t and repayments in month t. The indicator *ChargedOff* is set to 1 if a card that enters delinquency is eventually charged-off. We set the indicator *SyncedDelinqs* 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(0-7)* is an indicator that equals 1 for the months from t to $t + 7$, where $t = 0$ is the month that delinquency starts. In Column (1) we calculate *NetBorrowing* in a hypothetical scenario where, for the cases where *SyncedDelinqs*=1, borrowers max-out cards that 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 this case *CreditAvail* is 0 for DD cards after maxing out. In Column (2) we estimate the same model using the actual data. The last two rows present the coefficients and p-values from F-statistics that underlie the tests for strong and weak opportunistic borrowing, as per Equations 3 and 4 in the paper. Sample construction is described in Table 1.
Standard errors are clustered at the individual and year-month levels with p-values indicated by * <0.1; ** <0.05; *** <0.01.

Table 3: Tests for Opportunistic Borrowing: Heterogeneity

	(1) NetBorrowing	(2) NetBorrowing	(3) NetBorrowing	(4) NetBorrowing	(5) NetBorrowing	(6) NetBorrowing
IG × ChargedOff × CreditAvail (ζ_1)	0.023***	0.002	0.007	0.005	0.001	-0.132
	(0.008)	(0.005)	(0.006)	(0.006)	(0.005)	(0.087)
IG × SyncedDelinqs × ChargedOff × CreditAvail (ζ_2)	-0.045	-0.005	-0.041**	-0.014	-0.004	0.026
	(0.029)	(0.018)	(0.020)	(0.021)	(0.019)	(0.025)
IG × Post(0-7) × ChargedOff × CreditAvail (ζ_3)	-0.016*	-0.012*	-0.019***	-0.003	0.000	0.128
	(0.009)	(0.006)	(0.007)	(0.007)	(0.005)	(0.087)
IG × SyncedDelinqs × Post(0-7) × ChargedOff × CreditAvail (ζ_4)	0.051	0.013	0.038	0.027	0.001	-0.021
	(0.038)	(0.021)	(0.024)	(0.022)	(0.021)	(0.026)
Group Interaction (IG) Above Median	Utilization	Revolving Balance	Minimum Payment	APR	Holding Time	Previously ChargedOff
Individual × Month-by-Year Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	287,368	287,368	287,368	287,368	287,368	287,368
Adj. R^2	0.203	0.148	0.155	0.145	0.146	0.144
Δ Weak Opportunistic Borrowing (IG=1−IG=0) : $\zeta_1 + \zeta_2 + \zeta_3 + \zeta_4 = 0$	0.013	-0.002	-0.015	0.015	-0.001	0.001
Δ Weak Opportunistic Borrowing (IG=1−IG=0) p-value (two-sided)	0.669	0.809	0.181	0.148	0.903	0.878

This table examines the results for weak-form opportunistic borrowing depending on an indicator variable (IG), which takes the value of 1 if a specific variable for card j in month t is above the median for customer i in month t across all their cards, and 0 otherwise. In Column (1) the variable is utilization, in Column (2) revolving balance, in Column (3) minimum payment, in Column (4) the card's APR and in Column (5) the holding time of the specific credit card (since the card was first obtained). Variable definitions and sample construction criteria are as in Tables 1 and 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 from a two-sided test.
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: Tests for Opportunistic Borrowing: Stacked Regression Design

	(1) Max-Out Hypothetical Net Borrowing	(2) Actual Net Borrowing
CreditAvail (β_0)	0.053***	0.054***
	(0.002)	(0.002)
ChargedOff × CreditAvail (β_1)	0.019***	0.013***
	(0.006)	(0.004)
Post(0-7) × CreditAvail (β_4)	-0.035***	-0.036***
	(0.002)	(0.002)
Post(0-7) × ChargedOff × CreditAvail (β_5)	-0.023***	-0.017***
	(0.005)	(0.004)
SyncedDelinqs × CreditAvail (δ_0)	0.022**	0.019***
	(0.010)	(0.006)
SyncedDelinqs × ChargedOff × CreditAvail (δ_1)	-0.005	-0.012
	(0.013)	(0.009)
SyncedDelinqs × Post(0-7) × CreditAvail (δ_4)	-0.038***	-0.030***
	(0.010)	(0.007)
SyncedDelinqs × Post(0-7) × ChargedOff × CreditAvail (δ_5)	1.008***	0.016
	(0.012)	(0.011)
Individual × Month-by-Year × Stack Fixed Effects	✓	✓
Observations	4,191,699	6,172,156
Adj. R^2.	0.188	0.144
Strong Opportunistic Borrowing: $\beta_0 + \beta_1 + \beta_4 + \beta_5 + \delta_0 + \delta_1 + \delta_4 + \delta_5 = 1$	1.001	0.007
Strong Opportunistic Borrowing: p-value	0.031	0.000
Weak Opportunistic Borrowing : $\beta_1 + \beta_5 + \delta_1 + \delta_5 > 0$	0.999	-0.001
Weak Opportunistic Borrowing : p-value (one-sided)	0.000	0.543

This table presents the same analysis as Table 2 when we use a stacked regression procedure where we create one stack for each treatment (*ChargedOff*) using only clean controls, i.e., individuals that did not default over the sample period. Sample construction criteria are as in Table 1. *CreditAvail* 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 *CreditAvail* is negative we set it to zero. *NetBorrowing* is the difference between borrowing in month t and repayments in month t. The indicator *ChargedOff* is set to 1 if a card that enters delinquency is eventually charged-off. We set the indicator *SyncedDelinqs* is 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(0-7)* is an indicator that equals 1 for the months from t to $t + 7$, where $t = 0$ is the month that delinquency starts. In Column (1) we calculate *NetBorrowing* in a hypothetical scenario where, for the cases where *SyncedDelinqs*=1, borrowers max-out cards that 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 this case *CreditAvail* is set to 0 for DD cards after maxing out. In Column (2) we estimate the same model using the actual data. The last two rows present the coefficients and p-values from F-statistics that underlie strong and weak opportunistic borrowing, as per Equations 3 and 4 in the paper.
Standard errors are clustered at the individual and year-month levels with p-values indicated by * <0.1; ** <0.05; *** <0.01.

Table 5: Tests for Opportunistic Borrowing: Stacked Regression Design with Poisson Pseudo-Likelihood Specification

	(1) Discretionary Spending	(2) Repayment
CreditAvail (β_0)	0.000***	-0.000**
	(0.000)	(0.000)
ChargedOff × CreditAvail (β_1)	0.000	-0.000
	(0.000)	(0.000)
Post(0-7) × CreditAvail (β_4)	-0.000***	-0.000***
	(0.000)	(0.000)
Post(0-7) × ChargedOff × CreditAvail (β_5)	0.000***	0.000***
	(0.000)	(0.000)
SyncedDelinqs × CreditAvail (δ_0)	0.000*	0.000
	(0.000)	(0.000)
SyncedDelinqs × ChargedOff × CreditAvail (δ_1)	-0.000	-0.000
	(0.000)	(0.000)
SyncedDelinqs × Post(0-7) × CreditAvail (δ_4)	0.000	0.000
	(0.000)	(0.000)
SyncedDelinqs × Post(0-7) × ChargedOff × CreditAvail (δ_5)	-0.000	0.000
	(0.000)	(0.000)
Individual × Month-by-Year × Stack Fixed Effects	✓	✓
Observations	2,962,299	5,180,103

This table presents the same analysis as Table 2 when we use a stacked regression procedure where we create one stack for each treatment (*ChargedOff*) using only clean controls, i.e., individuals that did not default over the sample period. Additionally, instead of using absolute values (including zeros) as the outcomes, we use a Poisson Pseudo-Likelihood specification. Sample construction criteria are as in Table 1. *CreditAvail* 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 *CreditAvail* is negative we set it to zero. *Disretionary Spending* is spending excluding charges and fees in month t. *Repayment* are repayments in month t. The indicator *ChargedOff* is set to 1 if a card that enters delinquency is eventually charged-off. We set the indicator *SyncedDelinqs* is 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(0-7)* is an indicator that equals 1 for the months from t to $t + 7$, where $t = 0$ is the month that delinquency starts.
Standard errors are clustered at the individual and year-month levels with p-values indicated by * <0.1; ** <0.05; *** <0.01.

Table 6: Credit Card Outcomes around Delinquency

	(1) Discretionary Spending	(2) Charges and Fees	(3) Repayment	(4) Net Borrowing	(5) Utilization	(6) Net Utilization	(7) Credit Limit	(8) APR
ChargedOff	2.877	15.221***	15.485***	-12.598**	0.017	0.012	1003.228***	0.016***
	(7.988)	(2.387)	(5.336)	(5.136)	(0.010)	(0.022)	(159.668)	(0.002)
Post(0-7)	-53.968***	10.296***	-29.058***	-21.803***	0.020*	0.057**	47.879	-0.000
	(5.107)	(1.812)	(4.431)	(4.300)	(0.010)	(0.026)	(116.903)	(0.002)
Post(0-7) × ChargedOff	-1.103	0.238	-31.663***	30.355***	0.054***	0.181***	595.566***	0.001
	(8.042)	(2.496)	(5.243)	(6.249)	(0.012)	(0.033)	(163.886)	(0.002)
SyncedDelinqs	4.669	-1.499	3.683	-0.461	0.017	-0.036	317.219	-0.012**
	(17.180)	(3.792)	(10.509)	(12.126)	(0.018)	(0.037)	(321.109)	(0.005)
SyncedDelinqs × ChargedOff	8.526	4.248	2.664	9.442	-0.008	0.010	196.215	0.008**
	(12.488)	(3.428)	(9.304)	(7.250)	(0.015)	(0.035)	(226.755)	(0.004)
SyncedDelinqs × Post(0-7)	1.641	3.252	-9.549	13.297	0.015	0.129**	181.083	0.003
	(16.932)	(3.480)	(10.270)	(14.551)	(0.021)	(0.057)	(160.819)	(0.003)
SyncedDelinqs × Post(0-7) × ChargedOff	-13.183	-13.559***	10.131	-29.859***	-0.065***	-0.162***	-614.736***	0.003
	(12.659)	(3.804)	(9.225)	(8.241)	(0.017)	(0.044)	(179.392)	(0.003)
Individual × Month-by-Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Observations	301,526	301,526	301,526	301,526	287,368	289,165	301,392	294,580
Adj. R^2.	0.159	0.443	0.247	0.087	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 Tables 1 and 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 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	0.04
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. Variable definitions and sample construction criteria are as in Tables 1 and 2.

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)	
CreditAvail			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

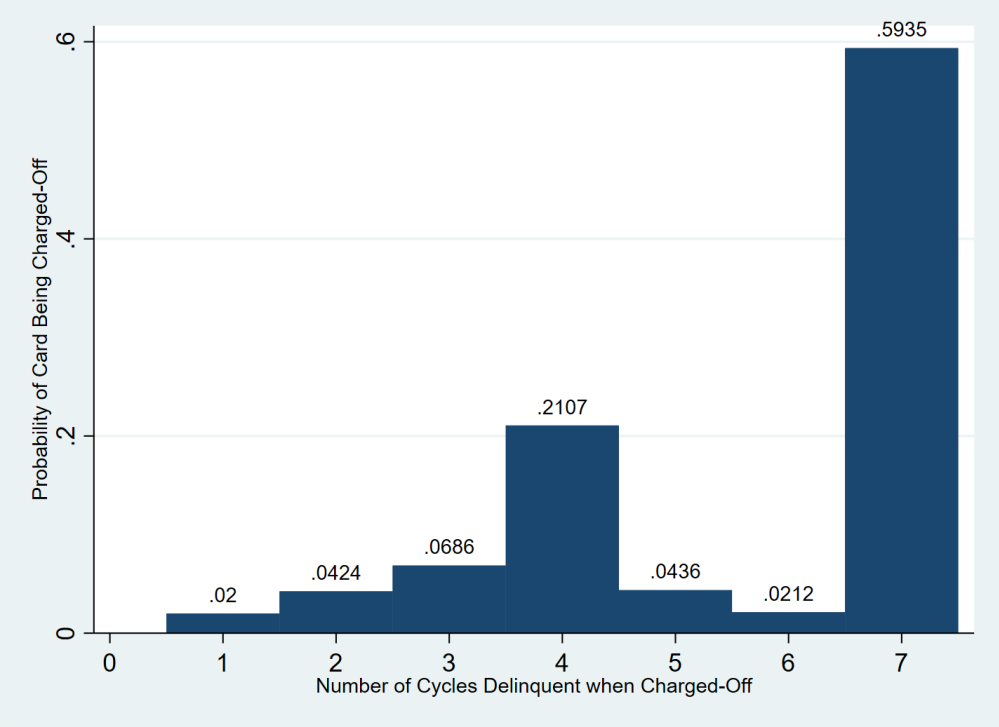
This table presents the results of predicting which card will default using different sets of card-specific variables. Variable definitions and sample construction criteria are as in Tables 1 and 2. *Mismatched Due Date* is an indicator of whether the credit card bill becomes due in weeks 2 and 3 of each month-by-year instead of in weeks 1, 4, or 5. *Card Age* is the number of months since the opening month-by-year of the card. In Column (4) we include dummy variables for 10 bins of each of the continuous variables.

Table 9: Structural Estimates

α	U_W	ρ
8.07	3.72	.028
(1.67)	(.512)	(.008)

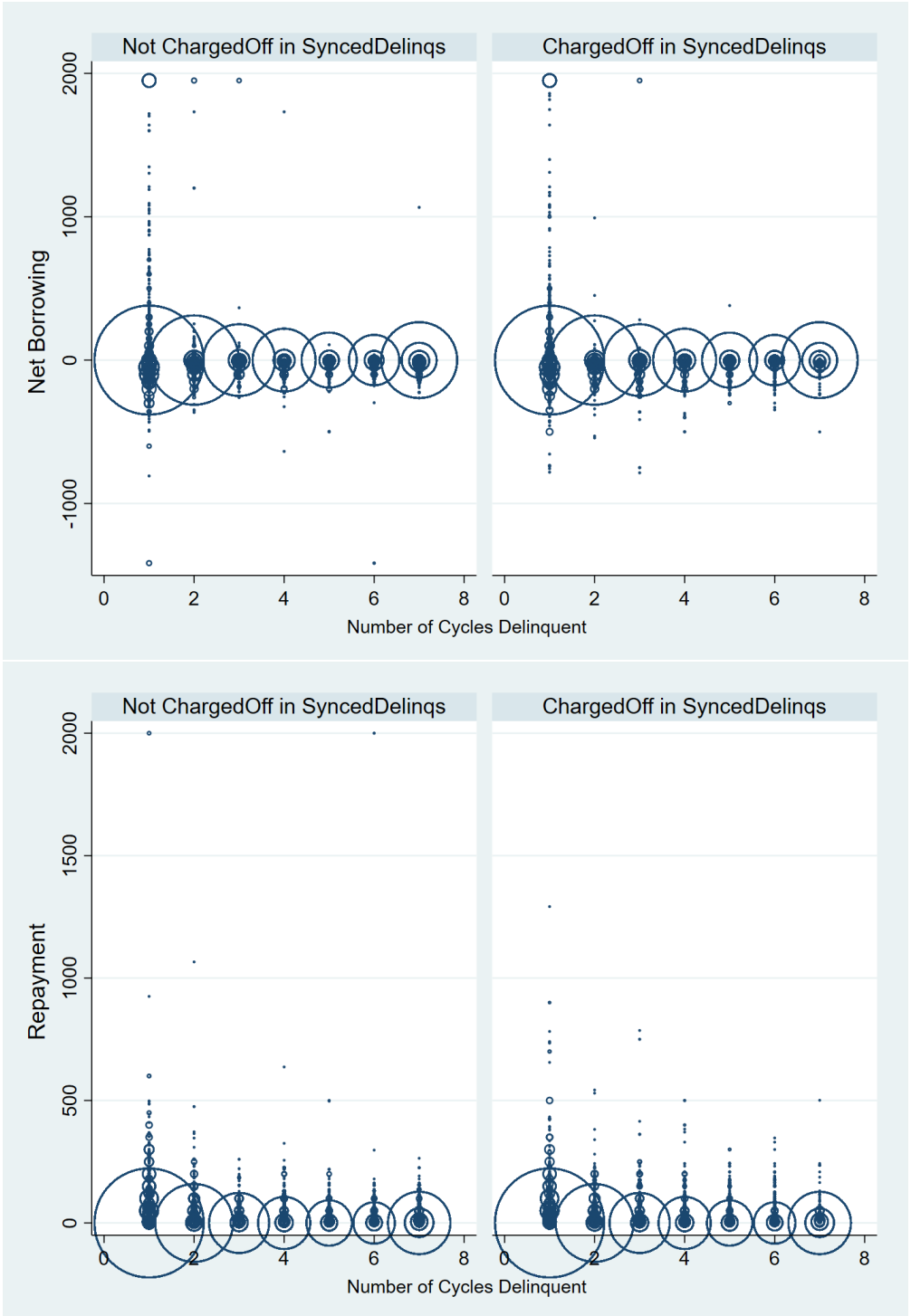
Standard errors are included in parenthesis. Further estimation details are included in Appendix B.

Figure 1: Months Delinquent When Card is Charged-Off



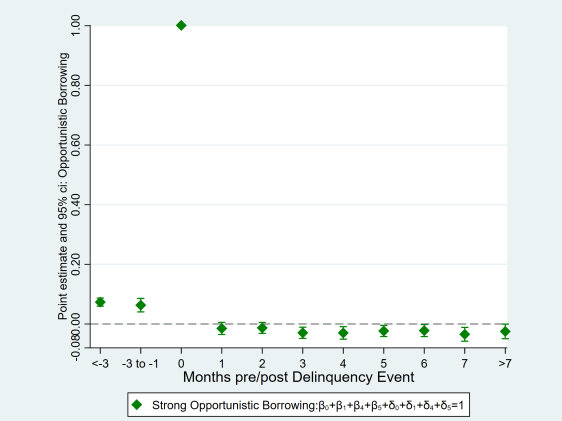
This figure shows the number of months a card is delinquent before being charged off by the credit card provider. This figure restricts to cards part of synchronious delinquencies.

Figure 2: Net Borrowing and Repayment for each Month Delinquent

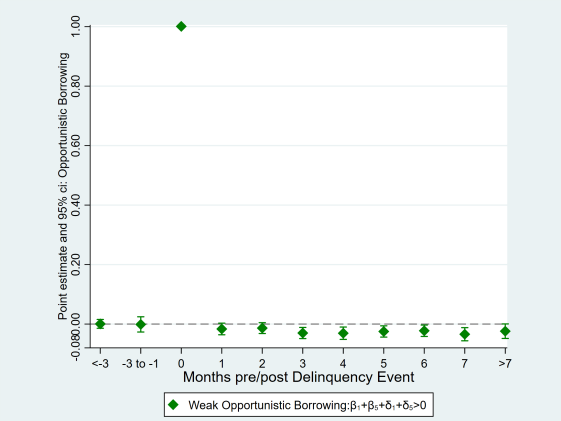


This figure shows the number of months a card is delinquent before being charged off by the credit card provider. This figure restricts to cards part of synchronous delinquencies.

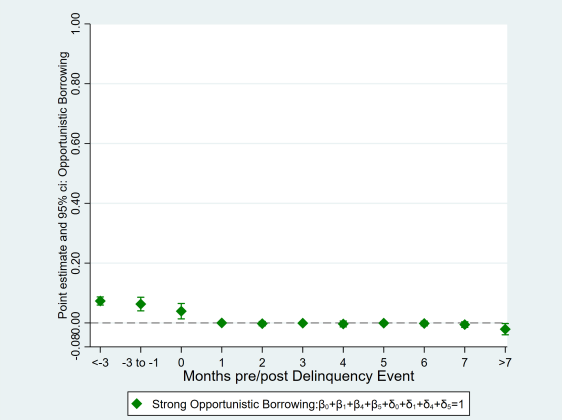
Figure 3: Tests for Opportunistic Borrowing: Dynamics



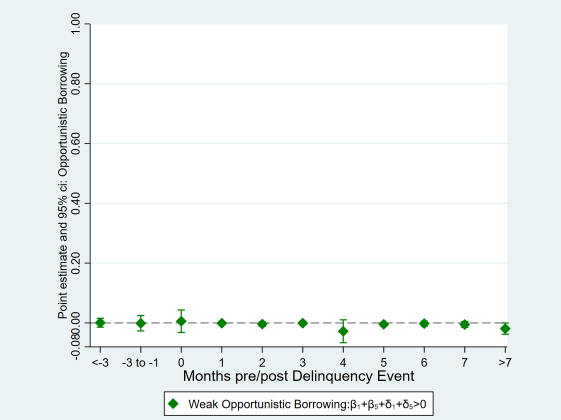
(A): Strong Test: Hypothetical



(B): Weak Test: Hypothetical



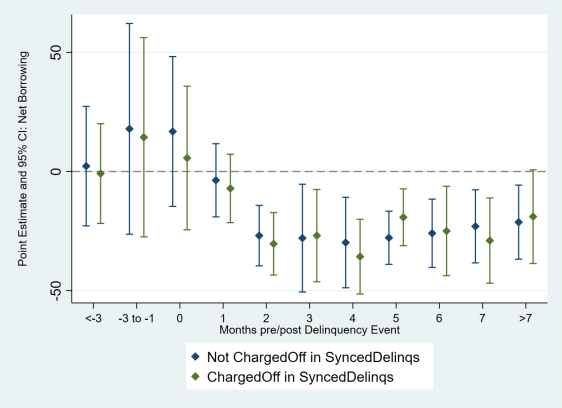
(C): Strong Test: Actual



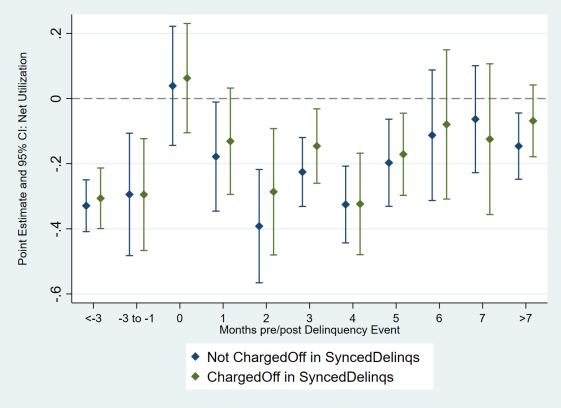
(D): Weak Test: Actual

These figures show dynamic tests of the strong and weak opportunistic borrowing hypotheses in each month around the start of delinquency for hypothetical and actual data (as in Table 2). Variable definitions and sample construction criteria are as in Tables 1 and 2. The models include borrower by year-month fixed effects, and the displayed standard error bars are obtained by clustering at the borrower and year-month levels.

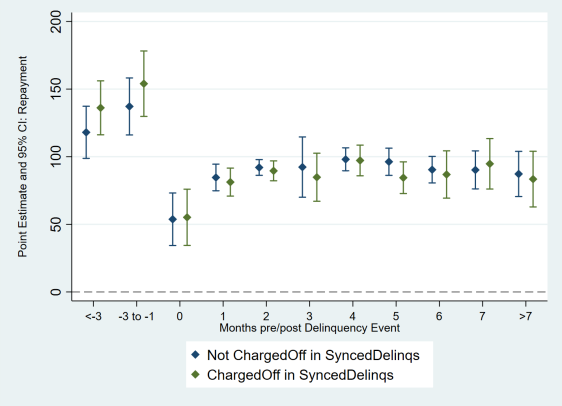
Figure 4: Margin plots Utilization and Net Utilization around Delinquency



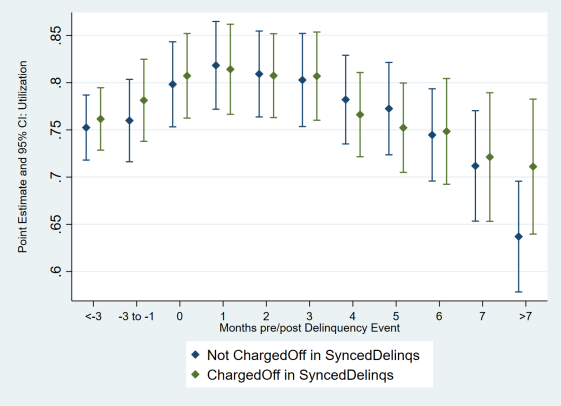
(A): Net Borrowing



(B): Net Utilization



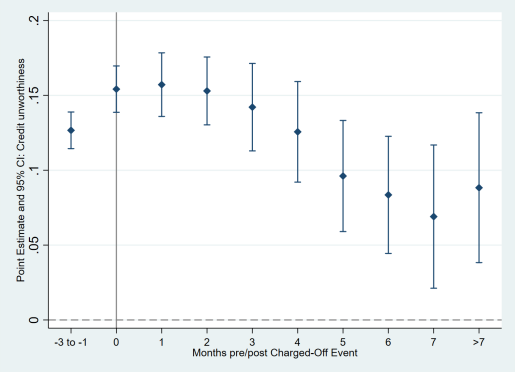
(C): Repayment



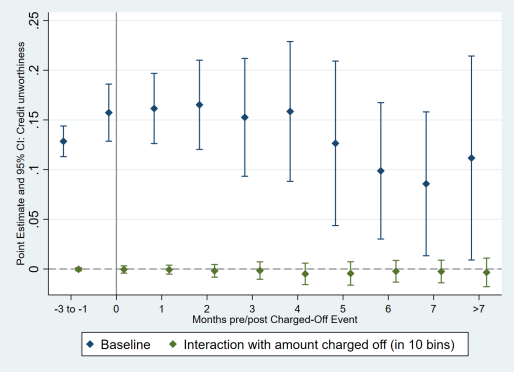
(D): Utilization

These figures show margin plots of the coefficients on the months around delinquencies for cards that are ultimately charged off versus not (when $SyncedDelinqs = 1$). 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*. Variable definitions and sample construction criteria are as in Tables 1 and 2. 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.

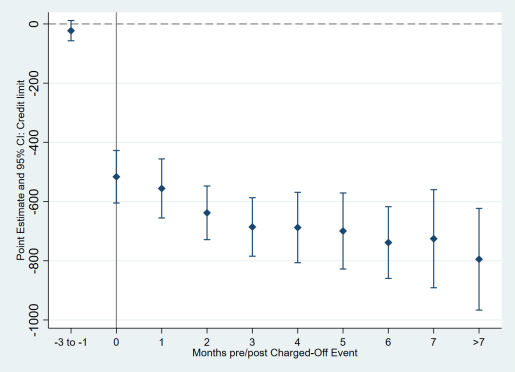
Figure 5: Dynamic Analysis of Credit Scores, APRs, and Limits around Charge-Off



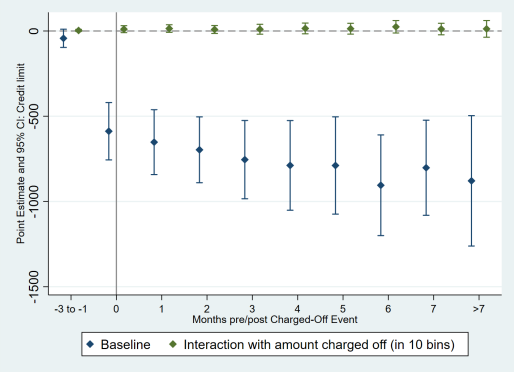
(A): Charge-Off Rate



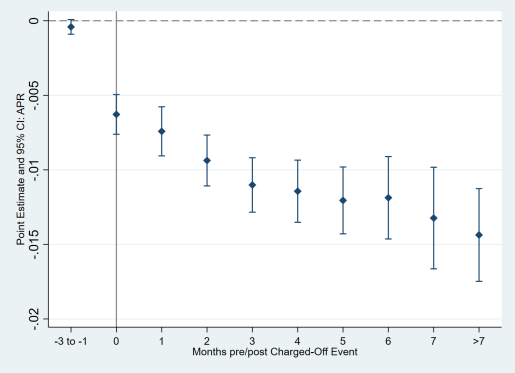
(B): Charge-Off Rate



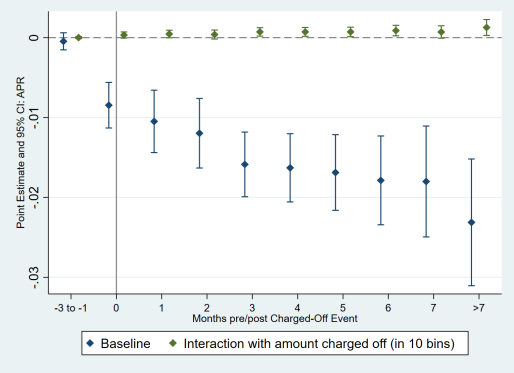
(C): Credit Limits



(D): Credit Limits



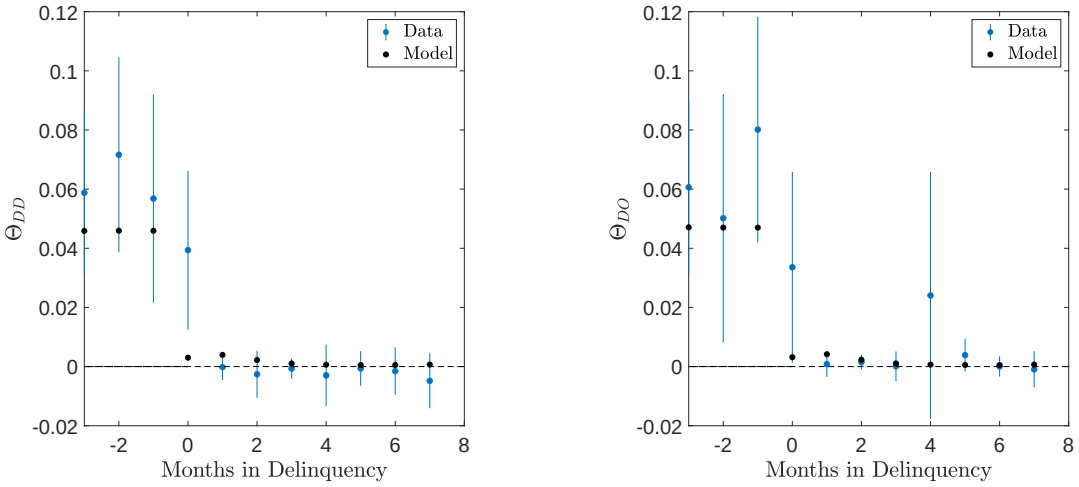
(E): APRs



(F): APRs

On the left side, these figures show the coefficients on the time dummies before and after a card of a given borrower was charged off. On the right side, the figures shows the baseline coefficients as well as the interaction coefficients with the amount charged off. The variable *Amount Charged-Off* is coded in 10 bins of amount charged off on the card that defaults. In Panels (A) and (B) the dependent variable is *Charge-Off Rate*, in (C) and (D) it is *Credit Limit*, and in (E) and (F) it is *APR*. Variable definitions and sample construction criteria are as in Tables 1 and 2. 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 6: Model Fit



(a) Fit of Strong Test Dynamics

(b) Fit of Weak Test Dynamics

Notes: Figure 6 plots the data moments $\Theta_{g,d}$ (same as in Figure 3 Panels (C) and (D)) against their model-implied counterparts. The blue dots in Panel (a) represent the empirical estimates of $\Theta_{DD,d}$ for each $d \in \{0, \ldots, 6\}$, while the black dots represent the model-implied values given the parameter estimates $\hat{\omega}$. Panel (b) is the analogous comparison of the empirical and model-implied values of $\Theta_{DO,d}$. The blue bars around each empirical moment denote 95% confidence intervals, where standard errors are clustered at the borrower-month level.

Figure 7: Rational Benchmark ($\alpha = 0$)

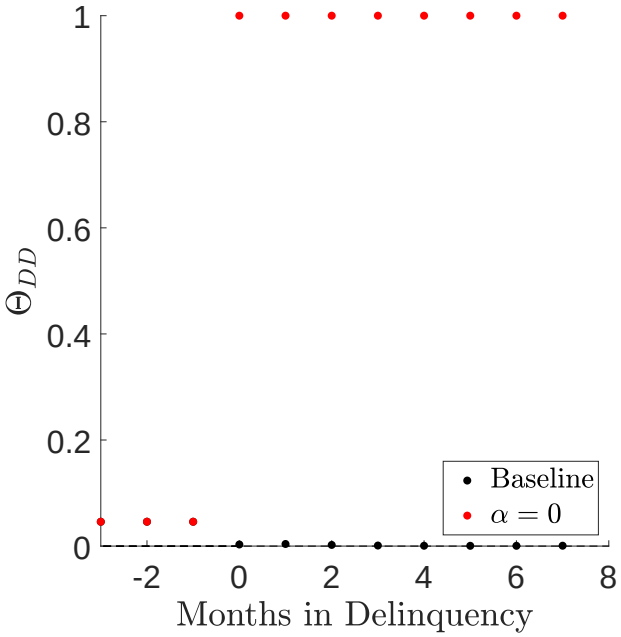
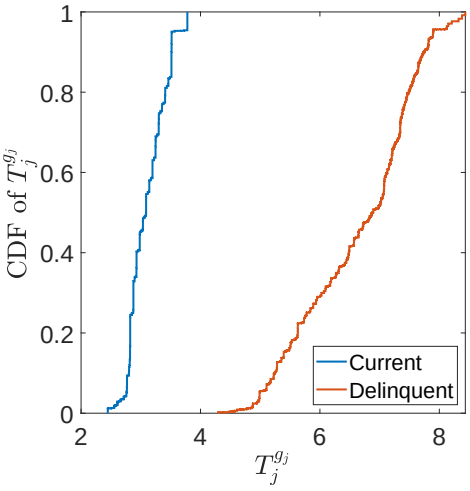
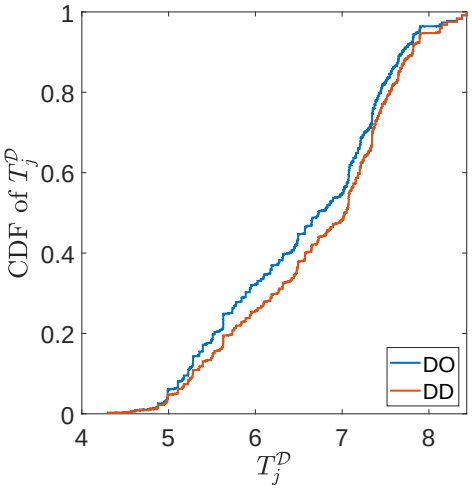


Figure 8: Implied Distributions of T_{ij}^{g}



(a) Current versus Delinquent



(b) DD versus DO

A Appendix

A.1 Model Appendix

Proof of Proposition 1. The Hamiltonian associated with continuing in delinquency is given by:

$$\mathcal{H} = u(c) + U_W\left(y - c + \sum_j s_j - \sum_{i\in\mathcal{C}} m_j B_j\right) + \sum_{j\in\mathcal{D}}\left(U_{B_j}(r_j B_j + s_j) + U_{d_j} + U_{H_j} m_j B_j + U_{F_j}\ell_j\right)$$
$$+ \sum_{j\in\mathcal{C}} U_{B_j}(s_j - \pi_j B_j) + \sum_{j\in\mathcal{D}} \lambda_j(d_j)(-\kappa_j - \alpha_j B_j + U(W, \mathcal{R}_j X) - U(W, X)) + \sum_j \nu_j(L_j - B_j - s_j)$$
$$+ \sum_j \xi_j s_j + \theta(W + \sum_j s_j - c) \tag{30}$$

where ν_j and ξ_j are KKT multipliers for the upper and lower bounds of the feasible s_{jt} set. θ is a KKT multiplier for the budget constraint. First order conditions for the continuous controls c and s_j are given by:

$$u'(c) - U_W - \theta = 0 \tag{31}$$

$$U_W + U_{B_j} - \nu_j + \xi_j + \theta = 0 \tag{32}$$

Equation (32) implies the following rule for optimal spending during delinquency:

$$s_{it} = \begin{cases} L_i - B_{it} & U_W + U_{B_i} + \theta_t > 0 \\ 0 & U_W + U_{B_i} + \theta_t < 0 \end{cases} \tag{33}$$

Note that the spending rule above holds regardless of whether card j is current or delinquent. Differences in spending in the two regimes will arise from difference in the curvature of U_{B_j} for delinquent and current cards. For each $j \in \mathcal{D}$, Equation (30) implies the following

envelope conditions:

$$\rho U_{B_j} = rU_{B_j} + U_{H_j} m_j - \lambda_j(d_j)\alpha_j - \nu_j - \lambda_j(d_j)U_{B_j} \tag{34}$$

$$(\rho + \lambda_j(d_j))U_{H_j} = 0 \tag{35}$$

$$(\rho + \lambda_j(d_j))U_{F_j} = 0 \tag{36}$$

$$\rho U_{d_j} = U_{F_j}\ell_j'(d_j) + \lambda_j'(d_j)(-\kappa_j - \alpha_j B_j + U(W, \mathcal{R}_j X) - U(W, X)) - \lambda_j(d_j)U_{d_j} \tag{37}$$

Equations (34) and (35) imply the following condition for delinquent cards:

$$-U_{B_j} = \frac{\alpha_j \lambda_j(d_j) + \nu_j}{\rho - r_j + \lambda_j(d_j)} \tag{38}$$

Noting that $\nu_j > 0$ if and only if $s_{jt} = L_j - B_{jt}$, we can rewrite the max out rule for delinquent cards as:

$$s_{it} = \begin{cases} L_i - B_{it} & u'(c_t) > \alpha_i \frac{\lambda_i(d_i)}{\rho - r_i + \lambda_i(d_i)} \\ 0 & u'(c_t) < \alpha_i \frac{\lambda_i(d_i)}{\rho - r_i + \lambda_i(d_i)} \end{cases} \tag{39}$$

For current cards, Equation (30) implies the following envelope condition:

$$\rho U_{B_j} = -m_j U_W - \pi_j U_{B_j} - \nu_j \tag{40}$$

Using Equation (33), the spending rule for current cards can then similarly be written as:

$$s_{it} = \begin{cases} L_i - B_{it} & u'(c_t) > U_W \frac{r_j + \pi_j}{\rho + \pi_j} \\ 0 & u'(c_t) < U_W \frac{r_j + \pi_j}{\rho + \pi_j} \end{cases} \tag{41}$$

□

Proof of Proposition 2. Under $F^{DD} \leq F^{DO}$, since $\Theta_g^{\mathcal{D}} = \mathbb{E}[S_\mu(T_{ij}^{\mathcal{D}}) \mid ij \in \mathcal{D}, ij \in g]$ and

$S_\mu(x)$ is non-increasing by definition, it follows that:

$$\mathbb{E}[S_\mu(T_{ij}^{\mathcal{D}}) \mid ij \in \mathcal{D}, ij \in DD] \leq \mathbb{E}[S_\mu(T_{ij}^{\mathcal{D}}) \mid ij \in \mathcal{D}, ij \in DO] \tag{42}$$

Thus, $\Theta_{DD}^{\mathcal{D}} \leq \Theta_{DO}^{\mathcal{D}}$. □

B Estimation Appendix

B.1 Standard Errors for Structural Estimates

For true parameter vector ω and consistent estimate $\hat{\omega}$, we have the following asymptotic distribution:

$$\sqrt{n}(\hat{\omega} - \omega) \to^d N(0, avar(\hat{\omega})) \tag{43}$$

$avar(\hat{\omega})$ can be expressed as:

$$avar(\hat{\omega}) = \left(\frac{\partial g(\omega)}{\partial \omega} W \frac{\partial g(\omega)}{\partial \omega'} \right)^{-1} \tag{44}$$

where $\frac{\partial g(\omega)}{\partial \omega}$ is the Jacobian of the moment residual $g(\omega) = \hat{\Theta} - \Theta^{model}(\omega)$ with respect to the structural parameters, W is the optimal weighting matrix. We approximate the Jacobian using:

$$\frac{\partial \hat{g}_m(\omega)}{\partial \omega_p} = \frac{g_p(\hat{\omega} + h_p) - g_p(\hat{\omega})}{h_p} \tag{45}$$

for each moment m and parameter p. h_p is the perturbation size for parameter which we set to 1% of the absolute value of the parameter estimate. The standard errors are the square root of the diagonal elements of the matrix:

$$\left(\frac{\partial \hat{g}(\omega)}{\partial \omega} \hat{W} \frac{\partial \hat{g}(\omega)}{\partial \omega'} \right)^{-1} \tag{46}$$

where $\hat{W}$ is the sample counterpart of the optimal weighting matrix.