Should Defaults be Forgotten?
Evidence from Legally Mandated Removal [*]

Marieke Bos[†]and Leonard Nakamura[‡]

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Abstract

Swedish law mandates the removal of negative credit arrears from credit reports after 3 years. We use a sharp discintunuity approach and find that the removal induces an abrupt improvement in the individuals' credit score that is not reversed in the longer run. Further, the excess loan applications caused by the boost in creditworthiness translates into significant new credit access.

We find evidence that only a minority of the individuals who received a negative credit arrear may be inherently high risk. Alternatively, our results may be interpreted as suggesting that removal of credit arrear may induce borrowers to exert greater effort along the lines of Vercammen (1995) and Elul and Gottardi (2007). Either interpretation opens the possibility that credit arrear removal is welfare enhancing.

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[†]Bos: SOFI, Stockholm University and The Swedish House of Finance; E-mail: Marieke.Bos@sofi.su.se

[‡]Nakamura: Research Department, Federal Reserve Bank of Philadelphia; E-mail: leonard.nakamura@phil.frb.org.

1 Introduction

In the last two decades the household credit buildup in the US and other developed countries like Sweden has been accompanied by rising rates of credit arrears and defaults. At any point in time in the last year approximately 9% of the US population and 6% of the Swedish population had an arrear on his or her credit file. Negative credit arrears can have serious consequences for the individual and their household. While credit scores fall, credit access is reduced if not closed in the Swedish case, which in turn can hamper the household's ability to smooth consumption in the face of job loss, unexpected health care expenses and other personal setbacks. To mitigate these negative effects most countries have laws that mandate the removal of negative information from credit bureau files after a certain retention period. In the US this is after seven years and after three years in Sweden. See figure 1 for similar provisions in other countries .

As Elul and Gottardi (2007) point out, forgetting a default typically makes incentives worse, ex-ante, because it reduces the punishment for failure. However, following a default it may be good to forget, because by improving an individual's reputation, forgetting increases the incentive to exert effort to preserve this reputation.

In this paper we examine empirically the consequences of the legally mandated removal of information. More specifically, we study with the aid of the sharp regression discontinuity approach the effects of removing credit arrears (the treatment) on consumers' credit scores, loan applications, credit access and future defaults. David Musto (2004) first explored the mandated removal of bankruptcy information from consumer's credit files. Unlike the bankruptcies studied by Musto, credit arrears however also include delinquencies that arise out of forgetfulness, accident, and legal disputes, rather than the inability or unwillingness to repay debt. This in combination with the incentives to exert effort to preserve the improved credit score after removal makes the net effect on the outcome ambiguous.

We find that the removal induces an abrupt improvement in the individuals' credit

score that is not reversed in the longer run. Further, the excess loan applications caused by the boost in creditworthiness translates into significant new credit access. We find that credit scores following the removal of the arrear remains significantly better over a two and half year period. If we accept the initial view of their credit score as being a reflection of their underlying type, then they do not revert to type, on average, and the forgetting appears to be correct. Thus it is not so clear-cut that the credit score prior to the removal of the arrear was an accurate reflection of the underlying type. Of course, credit arrears are less deliberate behavior than a bankruptcy declaration and may be thus less reflective of underlying type. Indeed, it suggests the possibility that for some proportion of the borrowers, the credit arrear may have been due to some accident or tremble that was not reflective of their underlying type, and that the fresh start may improve the accuracy with which these borrower types are reflected. It is possible that, in this case, lenders punish trembles that they cannot easily differentiate from the behavior of bad types.

On the other hand, the treatment group as a whole does acquire new arrears strikingly faster compare to a comparison group of individuals who didn't have an arrear for 10 periods. Overall, the treatment group is a worse group. These are grounds on which lenders would rightfully deny credit to the treatment group in the absence of the mandated arrear removal. Yet even in this group, roughly only 25 percent has another arrear after three years. That is, it appears possible that only a minority of the treatment group is sufficiently high risk so that a restoration of reputation does not induce them to act as if they were low risk. It is thus possible that removal of credit arrears has positive net welfare effects for a substantial fraction of borrowers. Within the frameworks of Vercammen (1995) and Elul and Gottardi (2007), it is possible that some form of credit arrear removal is socially justifiable.

The rest of the paper is organized as follows; Section 2 outlines the regression discontinuity approach. Section 3 summarizes the relevant legislation, Section 4 describes the data, and Section 5 takes a look at the effect of arrear removal on credit

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scores, loan applications and new credit access. Section 6 analyses default risk after initial removal, and Section 7 summarizes and concludes.

2   Regression Discontinuity

Following the notation by Angrist and Pischke (2009) we will use the Sharp Regression Discontinuity framework to make causal inference between the removal of credit arrears and our outcome variables Y_i. As stated earlier we will exploit the Swedish law that states that credit arrears in Sweden have to be removed from consumer credit reports after three years. We will call this legally enduces removal the treatment, D_i. This regression discontinuity design is described as *'sharp'* because the treatment is a deterministic and discontinuous function in the time that the arrear is on the individuals credit report

Our treatment D_i:

$$D_i = \begin{cases} 1 & if \ x_i \ \geq x_0 \\ 0 & if \ x_i \ \ < x_0 \end{cases} \tag{1}$$

, where $x_0 \ = 3 \ years \ of \ credit \ arrear \ on \ i's \ credit \ report$. Note that in this setting there is no value of time at which we can observe both treatment and control observations. Instead we will compare outcomes in a neighborhood of the discontinuity and assume that the trend in the outcome variables right before and after the arrear removal is not fundamentally changing other than the change caused by the removal.

A simple model formalizes this regression discontinuity approach;

$$E\ [Y_{0i} \mid x_i] \ = \ f(x_i)$$

where there is a discontinuity in the observed CEF, $E[Y_i \mid x_i]$ around the three year treshold, (see figure 1 to 4 for a conformation). While we assume that $f(x_i)$ is a nonlinear but reasonably smooth function. The regression discontinuity estimates are fitted by:

$$Y_i = f(x_i) + \rho D_i + \eta_i \tag{2a}$$

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where ρ is the causal effect of interest. and $D_i = 1(time\ of\ the\ arrear\ on\ the\ credit\ report \geq 3\ years)$. As long as $f(x_i)$ is continuous in a neighborhood of x_0 it is possible to estimate the model. As a robustness check we will narrow the area around x_0 and estimate a model using a so called placebo treatment.

We define the start of the treatment period for each individual within the remark-removal group uniquely as the period in which the remark is registered plus 17 periods.[1] The treatment indicator, T_{ct}, is set to one from the removal period onwards. In order to weight how many remarks an indvidual has left the treatment indicator, T_{ct}, is set to one devided by the maximum number of remarks obtained by the individual within the window of the panel minus 17 periods. To be precise, at time 0, for a given borrower who has not received a new credit remark within a three-year period, the credit remark received at time -17 is removed. When this occurs, we place in this case a $1/1 = 1$ from the start of the treatment onwards. For individuals who obtain more than one credit remark T_{ct} is always positive but smaller than one.

3   Credit arrears legislation

In general, a credit arrear is registered in Sweden by a credit bureau when debt is not paid back on time. As mentioned in the introduction, this includes both delinquencies that may arise out of forgetfulness, accident, and legal disputes, as well as more deliberate defaults. The credit bureau collects information on a daily basis from government institutions, such as the national enforcement agency, and the tax and transport authority and from private institutions such as banks. The minimum amount of a claim is a hundred kronor (~13 US dollars). The most common credit arrears are a decision by the national collection agency 'Kronefogden' or the cantonal

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[1] Due to the bi-monthly structure of the data removal after 3 years translates (depending on the timing of the receipt) in a 5 period in which removal occurs: period 17 to 21. We defined removal after 17 periods to optimize both simplicity of the rule and capturing the largest share of observed removals.

courts that there is an order for payment;[2] the abuse of bank accounts, credit or mortgages; tax claims; debt reconstruction; and repossession.

The relevant legislation on the registration and removal of credit remarks is outlined in the law on credit enquiries, 'Kreditupplysningslagen' (KuL).[3] KuL's primary goal is to protect the individual integrity of the individuals that are registered, but at the same time it also aims to contribute to an effective credit enquiry system. In paragraph 8 the law mandates that information on an individual who is not a businessmen should be removed at the latest three years after the day when the event occurred.[4] So the moment the credit bureau carries out the law, the credit report that potential creditors can observe loses all reference to the earlier delinquency. Compliance by credit bureaus in Sweden is monitored by the Swedish Data Inspection Board (datainspektionen).

Having a credit remark per se can have serious consequences; for example, it can prevent an individual from getting new credit, buying or renting an apartment or house or getting a telephone subscription or even a job.

4 Data description

The panel data employed for this article are a random sample of 15,683 individuals from the leading national credit bureau in Sweden, Upplysningscentralen (UC). UC is jointly owned by the Swedish banks; everyone who lives in Sweden legally and is 16 years or older is part of this registry. The panel tracks people for 36 bimonthly periods, over the nearly six years from February 2000 to October 2005. For these dates, we have the individuals' complete credit report, including 63 variables for each date. The credit report contains information supplied by the banks on unsecured

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[2]in other words the national collection agency or the court determined that someone is obliged to pay after he or she did not succesfully protest a claim.

[3]See SFS (1973:1173).

[4]For firms this is five years.

loans, indicating the number of current lines, usage, and limits. It also includes information on the number of requests for an individual's credit report that reflect applications for credit, the credit score, age, postal code, and marital status. The report also contains yearly information supplied by the Swedish tax authority on taxable income (subdivided into types of income: labor, entrepreneurship, capital and wealth). It also includes homeownership and the tax value of the real estate. Last, the credit report contains information on credit remarks–delinquencies and missed payments of debts, including tax liabilities and fines. This information is supplied by the national collection agency (Kronefogden) and the banks and is collected by the credit bureau.

In the analysis we focus on the individual's credit score, loan applications, total unsecured loans and defaults. The individual's credit score is measured on a scale of 0 to 100 as a probability of default. The probabilities of default are calculated with a model that has been estimated using the population of Swedish individuals 18 years and older. The sample period over which the model is estimated is unknown to us and the model is proprietary. The measure we use for loan applications is requests by financial institutions for the individual's credit report; these represent applications for credit at the financial institutions, including both secured and unsecured credit. The total unsecured loans consist of three kinds of unsecured loans observed in the data: credit cards,[5] regular credit lines and installment loans. The advantage of focusing on unsecured loans is that since they are not backed by collateral, creditors tend to rely more heavily on the creditworthiness of the applicant. Defaults are defined as obtaining a credit remark. All credit remarks are registered by the credit bureau but are supplied by both the national collection agency, Kronefogden, that handles both private and public claims and the banks that report credit abuse and defaults.

Within the window of the panel there are 562 individuals for whom we can observe

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[5]The Swedish credit card is like an American Express card – the borrower is expected to pay the balance each month.

both the receipt and the removal of their credit remark; we call these panelists the *'remark-removal'* group.

Descriptive statistics   Table 1 illustrates the descriptive statistics for the variables used in the regression for first, the total *'remark-removal'* group, second, for the periods where T_{ct} is equal to zero and lastly for the periods where the T_{ct} is equal to one. On average, the for less credit, especially in the period after the credit remark removal. They have slightly more loans both before and after credit remark removal, but the total limit is, on average, higher for the remark-removal group in the period after remark removal. The members of the remark-removal group use their outstanding credit to a higher extent, on average.

5   Arrear removal

When a credit arrear is erased from a consumer's credit report, the consumer's credit score improves (the estimated probability of bankrupcty falls). This creates additional incentives to apply for a loan, since the probability that the loan application will be successful has improved. We begin this section by establishing the existence of the initial effect of credit remark removal on credit scores. We will then follow the consumers to determine the empirical impact on the consumer's loan applications and the subsequent credit access. The analysis shows that consumers whose credit arrear was removed from their credit report because Swedish law mandates this after three years, receive additional credit, quite soon after removal, that they would not have received while this credit remark was still on their report.

Table 2 presents the regression discontinuity results of credit arrear removal. As expected the credit score change is on average over the whole treatment period negative ($\rho = -0.43$) although the overall average shows a positve trend ($mean = 0.07$).

To see how this increased creditworthiness leads to more credit, we first look at the individuals loan applications. In general, theory provides a rationale for borrow-

ers not being sure whether their applications for credit will be approved, even though the borrower's credit score is known to both the borrower and the lender. One such model is that the lender adds its private information about the creditworthiness of the borrower to the public score. See Nakamura and Roszbach (2010) for a model of this process for commercial loan borrowers that can be applied to household loans. From the perspective of the borrower, the lender's private information adds unobservable noise to the probability of receiving credit. Empirically, we observe that many applications for credit are in fact denied. This is prima facie evidence that borrowers are uncertain about whether they will receive credit, since, assuming that applications for credit have some cost, a borrower will apply for credit only if he or she perceives some probability of success.

The second column in tabel 2 shows the regression discontinuity results for the change in the number of loan applications.We find a positive coefficient for the treatment dummy, ($\rho = 0.02$) as expected. Then secondly we will look at the number, limit and outstanding balance of the individuals' total unsecured outstanding loans to check if the loan applications were successful on average. (respectively column 3, 4 and 5 of Table 2).

With an average of (XX) more loan applications arising per period in the years after the removal of the credit arrears we see an average of 0.07.change in new loans per period during the same period. The results for total limit and outstanding credit balances show an average increase per period of SEK 2329 and SEK 2280 respectively in the years following the removal. This is clearly an economically significant increase in credit access.

Thus access to additional credit translates into a substantial increase in credit usage. Therefore, we can conclude that the excess loan applications caused by the boost in creditworthiness indeed translate into significant new credit access for the individuals whose credit arrear is removed.

5.1 New arrears after removal

In the previous section we concluded that the excess loan applications caused by the boost in creditworthiness indeed translate into significant new credit access for the individuals whose credit remark is removed. Next we consider whether this increase in credit leads to more defaults (new arrears) down the road. To address this question we use a proportional cox hazard model to evaluate the risk off receiving a new credit arrear (defaulting on the individuals outstanding lines of credit) after the date of the previous exogenous credit arrear removal ($t > 0$).

For this analysis we need to define a contrast group that represents the 'regular' path. Defined as a path followed by individuals who did not experience an exogenous credit arrear removal within the window of the panel. As a start we will construct a 'contrast' group that is similar to the individuals in the 'arrear removal' group at the time they still had their credit arrear. Later on we will contruct a contrast group evaluated at the time right before the individuals from the arrear removal group received their credit arrear. We realize that the latter might be more appealing, however data contrains caused this group to be very small and thus the results less robust..The length of the window of our panel (6 years) in combination with the 3 years retention period before removal allowed only for 123 individuals where we could both observe the receipt and removal of their credit arrears (see appendix for analysis of this group).

5.1.1 Propensity score matching

In order to construct this 'contrast' group we will make use of propensity score match-

ing. That is, we start with estimating a probit model[6]

$$
\begin{aligned}
Y_c \quad = \quad & b_0 + b_1 Age_c + b_2 Inc_{c,y} + b_3 Inc_{c,y-1} + b_4 House\_value_c + .. \\
& b_5 Total\_no\_credit_c + b_6 Total\_limit_c + b_7 Total\_saldo_c + .. \\
& Score_c + \varepsilon
\end{aligned}
$$

,where the dependent variable Y_c is the variable that indicates if the individual belongs to the remark_removal group. The explanatory variables (the variables that we want the contrast group to be more similar in) are; age, yearly income, income the year before, value of the house owned, the total number, limit and saldo of the outstanding credit and finally the individuals credit $Score$, all evaluated right before the credit arrear removal. We fit the model for the sample that includes both the 'remark removal' group and the other individuals. We then use the individuals' propensity scores, which is simply the in-sample predicted probabilities to belong to the remark removal group to find the common support. The common support is the range of propensity scores/predicted-probabilities that occur both in the contrast as the remark removal group. We select only those individuals that fall within the common support range;1,849 panelist. We call this the 'contrast' group.

5.1.2 Hazard model

We estimate the following Cox proportional hazard model:

$$
\log \ h_i(t) = \alpha(t) + \beta x_i + \varepsilon_i \tag{3}
$$

or equivalently

$$
h_i(t) = h_0(t) + \exp(\alpha(t) + \beta x_i + \varepsilon_i)
$$

Here, $h_i(t)$ is the hazard rate o f individual i at time t, $\alpha(t) = \log h_0(t)$, and x contains all the time-varying covariates. The Cox model leaves the baseline hazard

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[6]We make use of program: psmatch2 within STATA in order to immidiately get the propensity score for every individual and not have to make the insample predicted probabilites seperately.

function unspecified, thereby making relative hazard ratios both proportional to each

other and independent of time other than through values of the covariates. In Table 3, we present the results from the Cox regressions where the dependent variable is the instantaneous risk of a default for the individual at time t, conditional on survival to that time.

First, column 1, Table 3 shows that overall the arrear removal group is more risky with a higher prevelance of default than the contrast group ($h_i(t) = 1.23$). Next, to find support for the argument that the arrear removal group is likely to consist of groups with a heterogeneous risk for defualting, we split the whole group into three sub-groups. Group 1; includes those individuals who might have received the initial arrear by a mistake/tremble with maximum one remark before exogenous removal (column 2). Secondly the intermediate group with those who had more than one but max 3 arrears (column 3). Finally the inherently risky group; with those individuals who had more than 3 arrears before exogenous removal (column 4).

5.1.3   Kaplan Meier survival estimates

Figure 8 shows the Kaplan-Meier survival estimates for the whole and the three sub-groups defined above.

6   Summary and Conclusions

Our first finding is that in the Swedish data, when credit arrears are removed, borrowers increase their applications for credit. Thus it would appear that these borrowers are at least somewhat aware of their credit scores and react to improvements in them.

Our second finding is that these requests for credit lead to new access to credit and additional borrowing. The new access to credit is quickly used.

Our third finding is that, similar to Musto, these borrowers' credit scores worsen after the new access to credit. As requests for credit lead to worsening credit scores,

this is not surprising.

A key difference between our work and that of Musto is that Musto finds that over a three year period, credit scores are significantly worse following the removal of the bankruptcy flag than they would have been otherwise, despite the immediate initial improvement in the scores that occurs as a result of forgetting. If we accept the view that their initial credit score reflects their underlying type, then they revert to type, on average, and the forgetting appears to be in error.

In our case, the credit score following the removal of the remark remains significantly better over a 18-month period and is not significantly worse even after four years. Thus it is not so clear-cut that the credit score prior to the removal of the remark accurately reflected the underlying type. Of course, credit remarks reflect less deliberate behavior than a bankruptcy declaration and therefor they may be less reflective of underlying type.

Indeed, it suggests the possibility that for some proportion of the borrowers, the credit remark may have been due to some accident or tremble that was not reflective of their underlying type, and that the fresh start may improve the accuracy with which these borrower types are reflected. It is possible that, in this case, lenders punish trembles that they cannot easily differentiate from the behavior of bad types. Alternatively, there is the possibility that individuals who experience remark removal may have an amplified incentive to exert effort, and that increased effort reduces the likelihood that they will experience a new credit remark. This latter interpretation would suggest that the theories of Vercammen (1995) and Elul and Gottardi (2007) may be applicable to credit remark removal, and that credit remark removal may be a socially beneficial policy.

References

[1] Boyes, W., D. Hoffman, and S. Low (1989), "An Econometric Analysis of the Bank Credit Scoring Problem," Journal of Econometrics, 40, 3-14.

[2] Elul, Ronel, and Piero Gottardi (2007), "Bankruptcy: Is it Enough to Forgive or Must We Also Forget?" F*ederal Reserve Bank of Philadelphia Working Paper No. 07-10.*

[3] Hunt, Robert M. (2006), "Development and Regulation of Consumer Credit Reporting in the United States," in Giuseppe Bertola, Richard Disney and Charles Grant, *The Economics of Consumer Credit*, MIT Press, Cambridge, MA, 301-345.

[4] Jappelli, T. and M. Pagano (2006). "The Role and Effects of Credit Information Sharing". In Giuseppe Bertola, Richard Disney and Charles Grant, *The Economics of Consumer Credit*, MIT Press, Cambridge, MA

[5] Musto, David K. (2004), "What Happens When Information Leaves a Market? Evidence from Postbankruptcy Consumers," The Journal of Business, 77(4), 725-748.

[6] Nakamura, Leonard I. and Roszbach, Kasper F. (2010), "Credit Ratings and Bank Monitoring Ability," FRB of Philadelphia Working Paper No. 10-21.

[7] SFS (1973:1173), https://lagen.nu/1973:1173

[8] Vercammen, J. A. (1995), "Credit bureau policy and sustainable reputation effects in credit markets.Economica", 62 (248), 461–478.

A Tables and Figures

Figure 1
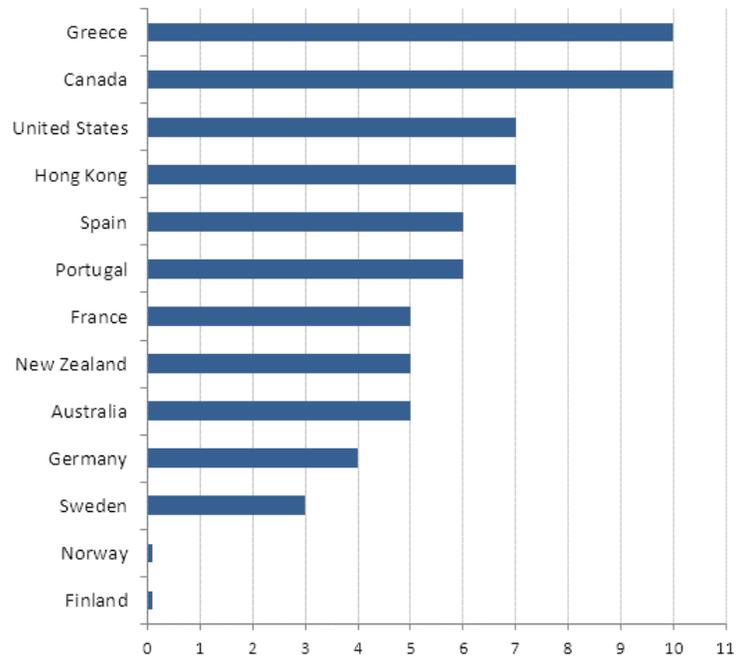**Retention times for negative credit remarks**
in years

Figure 2
Discontinuity in Credit Scores
Before and after negative credit remark removal

Note.-There are 562 panelists from the remark-removal group who lose their final credit arrear between 01Feb2000 and 01Oct 2005.

For panelist C of these 562, we set loseremark D_{ct} to 1 at t=0 defined to be the first month without a credit arrear. Hence S$_{c}$, event

time, differs among the panelists. The blue colored dots _p25, _p50, _p75 and _p100_score represent respectively the mean credit

score in the randomely assigned quintiles.

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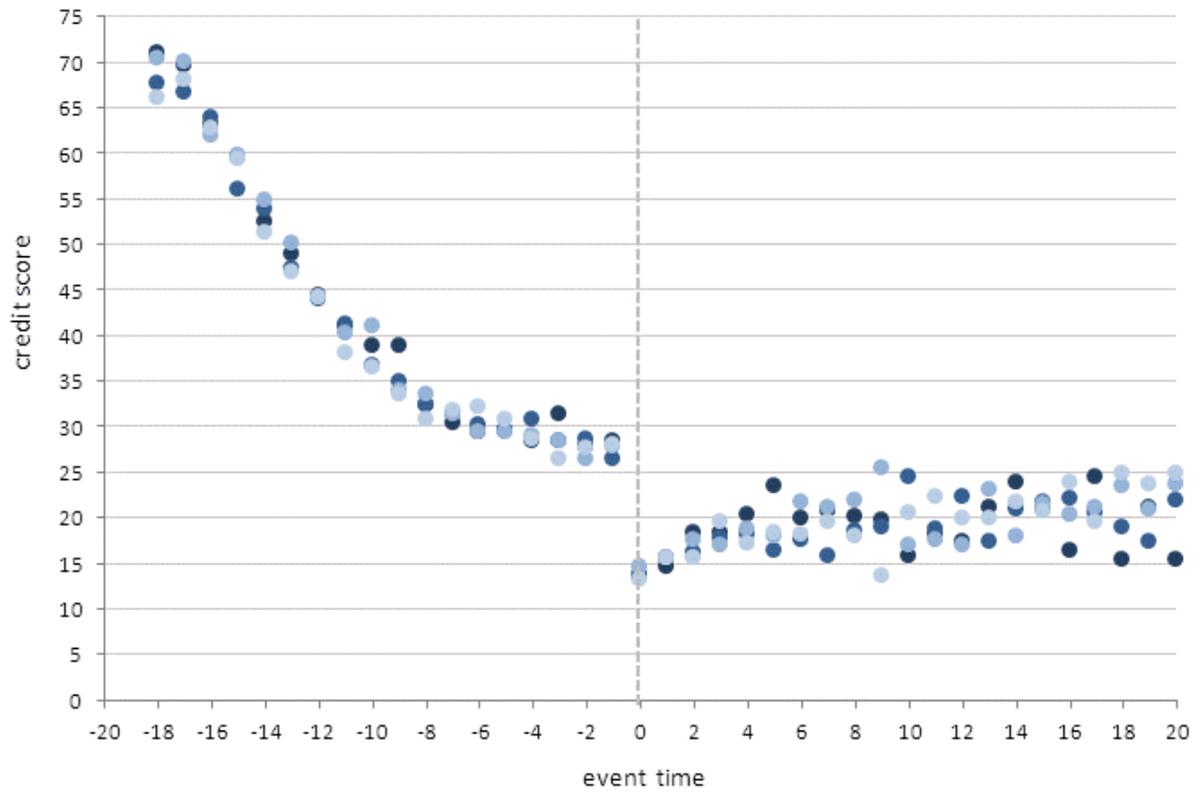**Figure 3A, B, C, D**

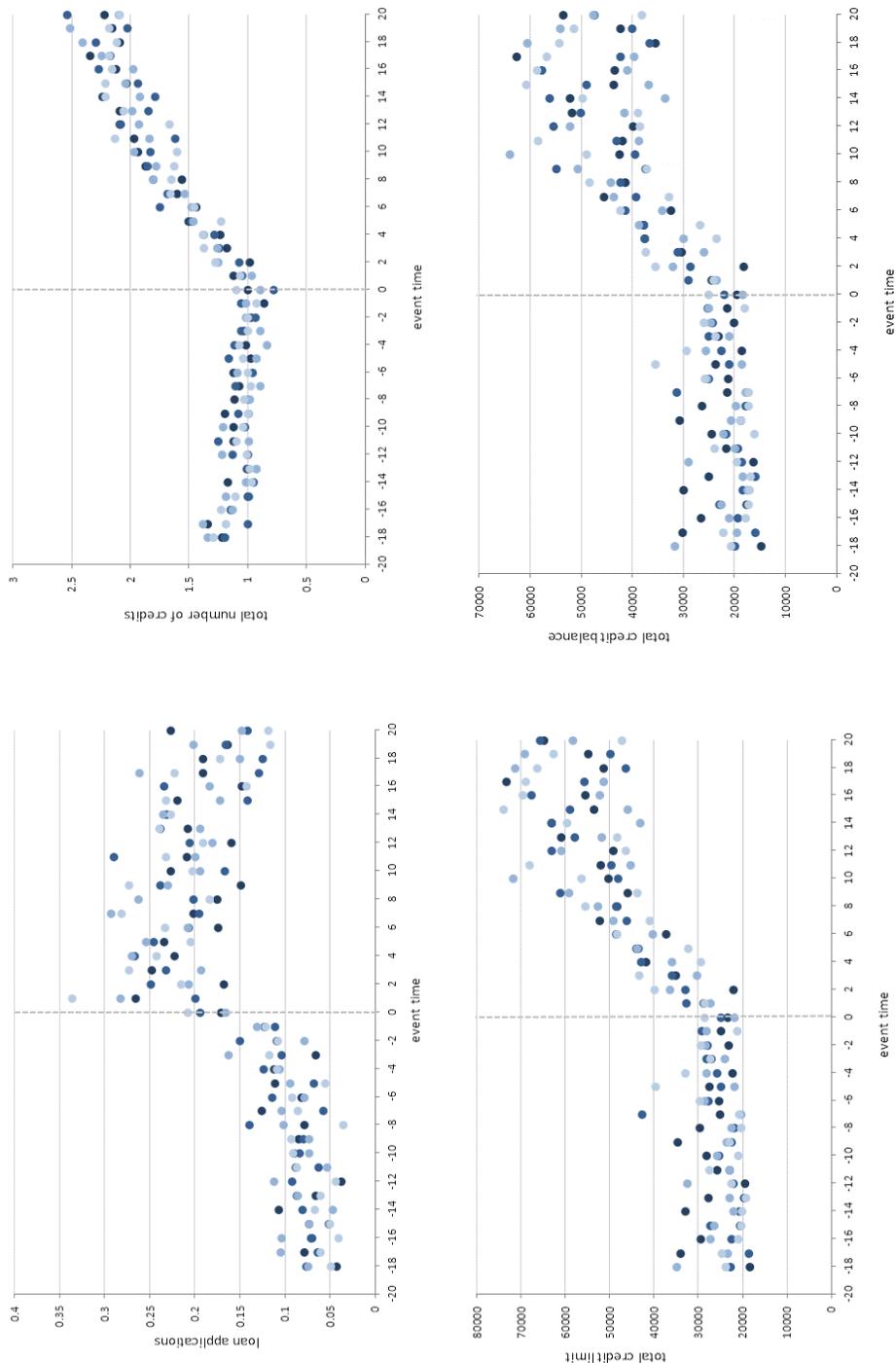**Credit before and after negative credit remark removal**

Figure 4
Kernel Density graph
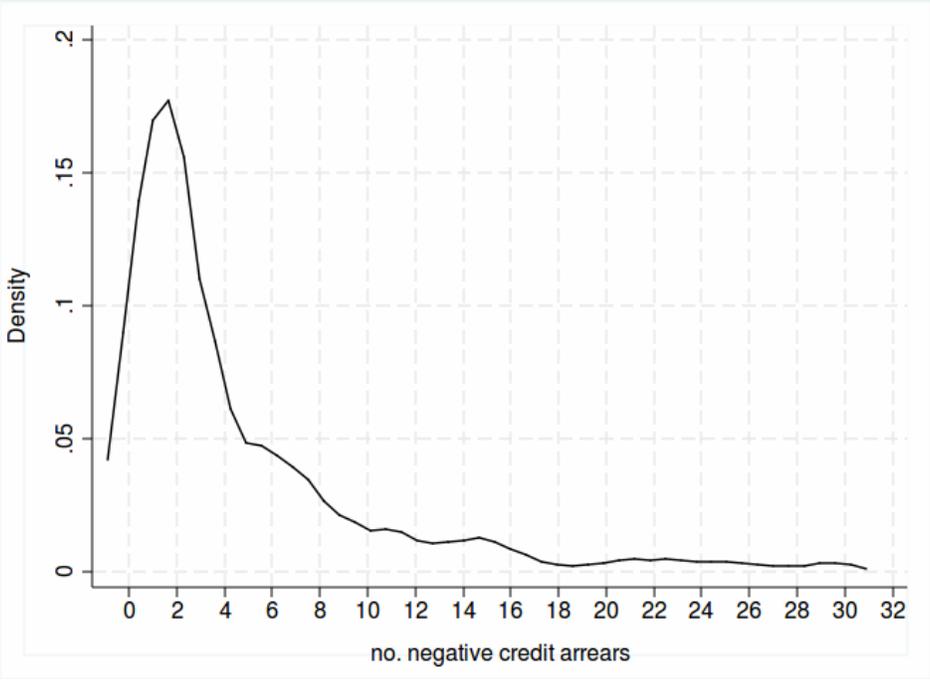**Number of credit arrears before the first credit arrear removal.**

Figure 5
Kaplan-Meier Survival graph
Percentage of individuals without a new credit arrear
After credit arrear removal

For three groups of individualis Group 1 (highest dotted line) consist of individuals who have had only one arrear in the period leading up to the removal of the final remark at time S_c. Group 2, (the middle solid line) consist of indiviudals who have had more than one arrear, but a maximum of three arrears. Finally group 3, (the lowest stretched dotted line) consist of individuals who have had more than three arrears in the period leading up to the removal of the final remark.

Note.- There are 562 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist C of these 562, we set loseremark S_c to 1 and define t=0 to be the first month without any credit arrear. For the panelist from the contrast group we use propensity score matching to predict the likelihood to belong to the remark_removal group based on personal characteristics described in paragraph XX. The matched panalist from the contrast group will take the same fictional removal day as its counterpart in the remark_removal group.
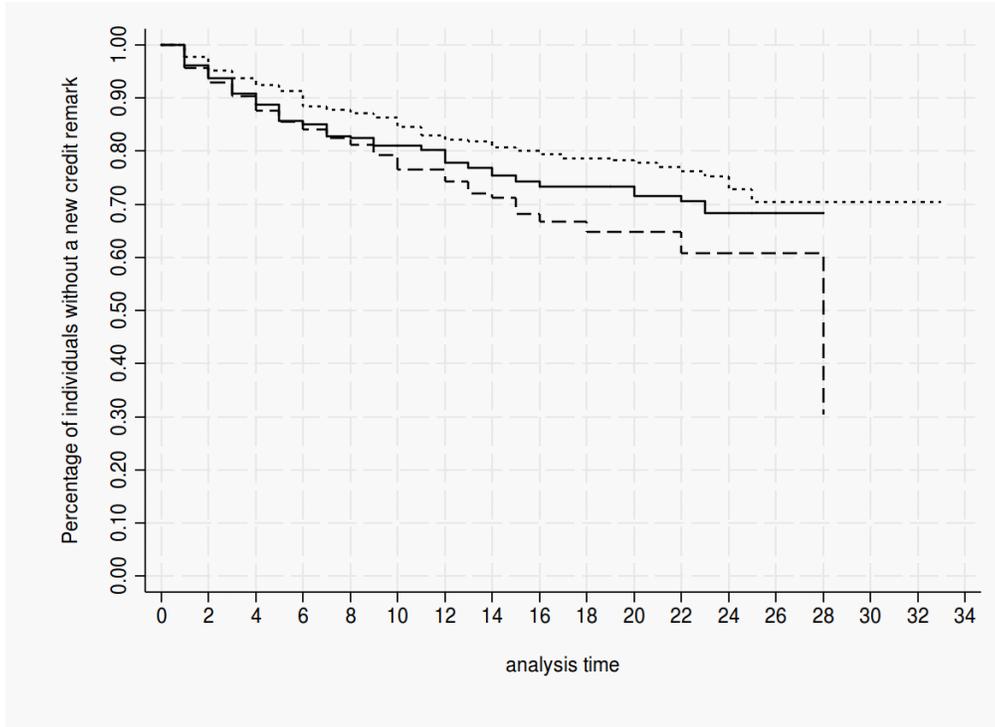
Table 1
Descriptive statistics
Remark-removal group
Before and after credit arrear removal

Note.- Everyone who receives one or more credit arrears within the first 19 periods of the panel belongs to the remark_removal group. There are 548 panelists from the remark-removal group for whom we observe their remark removal between 01Feb2003 and 01Oct 2005 ther remainder 14 people either die or emigrate and therefor have too short a panel to observe their removal.

	Mean	std. Dev.	Min	Max	Obs.	Individuals
remark_removal group						
credit score	43.83	35.82	0.25	99.92	23710	562
loan applications	0.13	0.48	0.00	12.00	23710	562
total no credit	1.23	1.73	0.00	19.00	23710	562
total limit	28252.50	85884.33	0.00	3490279.00	23710	562
total credit balance	27430.90	80049.02	0.00	3490279.00	23710	562
treatment = 0						
credit score	50.02	35.25	0.25	99.92	16423	562
loan applications	0.11	0.44	0.00	9.00	16423	562
total no credit	1.31	1.81	0.00	19.00	16423	562
total limit	28782.49	85288.57	0.00	246435.00	16423	562
total credit balance	28066.54	76565.55	0.00	2415308.00	16423	562
treatment = 1						
credit score	29.89	33.07	0.39	99.89	7287	548
loan applications	0.16	0.57	0.00	12.00	7287	548
total no credit	1.05	1.54	0.00	13.00	7287	548
total limit	27058.00	87206.18	0.00	3490279.00	7287	548
total credit balance	25998.33	87380.84	0.00	3490279.00	7287	548

Table 2
Regression discontinuity
Credit arrear removalT

Dependent variable	[1] d.score	[2] d.loan_applications	[3] d.total_no_credit	[4] d.total_limit	[5] d.total_credit_balance
treatment all periods	-0.43*** [0.00]	0.02*** [0.00]	0.07*** [0.00]	2328.85*** [0.00]	2280.25*** [0.00]
Treatment effects over time since first arrear removal					
First two months	-3.45*** [0.00]	0.041 [0.16]	-0.02 [0.16]	-1811.07 [0.28]	143.84 [0.90]
First half year	-2.25*** [0.00]	0.01 [0.25]	-0.02 [0.10]	-970.42 [0.41]	-186.84 [0.83]
First year	-1.72*** [0.00]	0.02*** [0.00]	0.02* [0.07]	-189.54 [0.80]	367.07 [0.57]
First one and half years	-1.04*** [0.00]	0.03*** [0.00]	0.04*** [0.00]	1588.23** [0.02]	1765.23*** [0.01]
Frst two years	-0.73*** [0.00]	0.02*** [0.00]	0.05*** [0.00]	1701.72** [0.03]	1731.69** [0.03]
First two and half years	-0.46*** [0.00]	0.02*** [0.00]	0.07*** [0.00]	2204.96*** [0.00]	2108.74*** [0.00]
mean	0.07	0.04	0.05	853.74	399.73
time fixed effects	yes	yes	yes	yes	yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	516,996	516,996	516,996	516,996	516,996
individuals	15,245	15,245	15,245	15,245	15,245

Table 3
Regression discontinuity Credit arrear removal

Dependent variable	[1] d.score	[2] d.loan_applications	[3] d.total_no_credit	[4] d.total_limit	[5] d.total_credit_balance
Treatment for everyone	-0.43***	0.02***	0.07***	2328.85***	2280.25***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Treatment effects for individuals with max number of credit arrears in the period before first removal					
one credit arrear	-1.05***	0.02	0.08**	926.99	705.45
	[0.00]	[0.14]	[0.02]	[0.67]	[0.75]
two credit arrears	-0.71**	-0.01	0.03**	4444.59	4122.63
	[0.03]	[0.14]	[0.03]	[0.23]	[0.26]
three credit arrears	-0.16	0.03***	0.07***	1630.45***	1718.45**
	[0.65]	[0.00]	[0.01]	[0.01]	[0.02]
More than three credit arrears	-0.29	0.02***	0.08***	1983.92***	1999.19***
	[0.15]	[0.00]	[0.00]	[0.00]	[0.00]
mean	0.07	0.04	0.05	853.74	399.73
time fixed effects	yes	yes	yes	yes	yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	516,996	516,996	516,996	516,996	516,996
individuals	15,245	15,245	15,245	15,245	15,245

Table 4

Cox regressions on new defaults after Credit arrear removal

The Breslow method has been used for tied observations

Note.- There are 1179 panelist from the "arrear removal" group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist C of these 1179, we set D_c to 1 and define t=0 to be the first month without the credit remark. For the 1879 panelist from the "contrast" group t= 0 to be defined as the fictional removal equal to the individual from the arrear remove group where the individual from the contrast group is matched to.

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B   Appendix

Lender   In providing credit to a consumer, the lender seeks to maximize profit, subject to free entry and to the regulatory restrictions on the information to be used in the credit application. We assume that lenders may have unique access to information, so that free entry will not necessarily result in an expected zero profit. The regulatory restrictions are unmodeled, although they might be justified using, for example, the theory in Elul and Gottardi (2007).

The likelihood that the lender j will be repaid on a loan of fixed size to borrower i is based on the lender's knowledge of publicly and privately available credit information, which can be summarized in two vectors at time t, private information, X_{ijt}, and the public information available about an individual borrower, Y_{it}, and both are subject to regulatory restrictions. These restrictions might include anti-discriminatory requirements (such as race may not be considered when reviewing a loan application) or requirements that data beyond some fixed period in the past be ignored. Lender j calculates the probability of bankruptcy

$$\rho_{ijt} = R\left(Y_{it,}X_{ijt}\right)$$

This information is, moreover, subject to random errors that arise from processing. (For a discussion of errors in credit information, see Hunt, 2006.) The existence of errors and of private information, which may arise from the lender's previous or ongoing relationship to the borrower, implies that the borrower has incomplete information about the likelihood and will form only a partial view of the likelihood of obtaining credit, if credit is applied for.

As time passes, Y_{it} and X_{ijt} change, and as a result of the regulatory restrictions, they may change in predictable ways. As a consequence, ρ_{ijt} may not be a martingale.

Consumer   Each application for credit has a cost, which is assumed to be fixed across individuals at C. Having more credit has a benefit, which varies from borrower to borrower. A borrower applies for credit if the expected benefit of more credit from the application exceeds the cost. Formally, we can, without loss of generality, normalize the credit rating of the borrower to the interval 0 to 1, as the probability that the loan application will be successful, π_i. The expected benefit for credit is defined to be B_i. Then the expected net benefit of a single credit application is

$$EA_i = max(\pi_i B_i - C, 0)$$

A credit application will be made if $EA_i > 0$

If an exogenous improvement in the credit rating occurs, this will result in an increase in the demand for credit from 0 to 1 if $EA_i = 0$ before the increase in the credit rating and $EA_i > 0$ after the increase.

This will tend to imply that the increase in credit applications will depend on its impact on the probability of receiving credit, although this response could be nonlinear and need not be monotonic. Note that for each borrower, there is a probability of receiving credit that is just sufficient to result in a credit application. Thus for any given credit rating, there is a probability that a borrower will apply for credit, which depends on the variation across borrowers in the benefit of credit.

In general, theory provides a rationale for borrowers not being sure whether their applications for credit will be approved, even though the borrower's credit score is known to both the borrower and the lender. One such model is that the lender adds its private information about the creditworthiness of the borrower to the public score. See Nakamura and Roszbach (2010) for a model of this process for commercial loan borrowers that can be applied to household loans. From the perspective of the borrower, the lender's private information adds unobservable noise to the probability of receiving credit. Empirically, we observe that many applications for credit are in fact denied. This is prima facie evidence that borrowers are uncertain about whether they will receive credit, since, assuming that applications for credit have some cost, a borrower will apply for credit only if he or she perceives some probability of success. If the extent of credit tightening can be measured as a probability of receiving credit at any given credit rating, then this study allows an approximate measure of the extent to which credit tightening will result directly in a decline in the quantity of credit applications.

Possible optimality of credit remark removal We have two complementary views of the value of credit remark removal. One is that credit remarks include what we have referred to as "trembles." To be concrete, consider a borrower who fails to pay a bill that arrived while the borrower was on an extended vacation. If extended vacations are rare, the borrower may not have foreseen the potential for a bill falling due while he or she was away. If these trembles are hard to distinguish from, say, income or liquidity shocks that represent more permanent characteristics of the borrower, then periodically cleaning the slate of borrowers who have few such trembles or shocks may be optimal.

Another view is that the desire to pool with safer borrowers may increase the incentives of riskier borrowers to exert more effort. Vercammen (1995) has pointed out that truncating the storage of credit histories may have positive welfare benefits by inducing such effort. Elul and Gottardi (2007) specifically use the probability of forgetting an episode of bad credit to investigate the conditions under which a given probability of forgetting may be optimal.