Should Credit Remarks be Forgotten? Evidence from Legally Mandated Removal *

Marieke Bos[†] and Leonard Nakamura[‡]

November 2010

Abstract

Swedish law mandates the removal of credit remarks from credit reports after 3 years. 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 credit remark may be inherently high risk. Alternatively, our results may be interpreted as suggesting that removal of credit remarks 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 remark removal is welfare enhancing________________________________

JEL classification: C34, C35, D63, D81, G21

Keywords: Consumer credit, Lending policy, Credit Scoring.

---

*We are indebted to Elif Sen for providing outstanding research assistance, and grateful for comments from Kasper Roszbach. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Executive Board of the Federal Reserve Bank of Philadelphia, or of any other person associated with the Federal Reserve System.

†Bos: SOFI, Stockholm University; 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 this paper, we study a topic first explored by David Musto (2004): the effect of a legally mandated removal of consumer credit information from consumer credit files. The removal of credit remarks from Swedish credit bureau files occursafter three years. Similar provisions exist in most other countries.[1] 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. They show theoretically that whether forgetting is optimal depends on the relative strength of the borrower's incentives, the average quality of the borrower, the loss of output and the patience of the agents. In this paper we examine empirically the consequences of the legally mandated removal of information. More specifically, we study the short- and long-run effects of removing credit remarks on consumers' credit scores, loan applications, credit access and defaults.

Unlike the bankruptcies studied by Musto, credit remarks also include delinquencies that may arise out of forgetfulness, accident, and legal disputes, rather than the inability or unwillingness to repay debt. As a result, it is possible that the removal of this information may have a more ambiguous effect on outcomes. We therefore consider that the remark-removal group consists of two subgroups, one that obtained a remark because group members are inherently bad types, and one that obtained a remark because group members experienced a random accident or tremble, which will not be repeated.

A key difference between our work and that of Musto is that Musto finds that credit scores eventually are significantly worse following the removal of the bankruptcy flag than they would have been otherwise over a three-year period, despite the initial immediate improvement in the scores as a result of forgetting. If we accept the initial

[1] See Elul and Gottardi (2007) and Japelli and Pagano (2006) for a comparison.

view of their credit score as being a reflection of 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 was an accurate reflection of the underlying type. Of course, credit remarks 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 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.

On the other hand, with respect to the comparison groups, whose members did not have a credit remark for 10 periods, the remark-removal group does acquire remarks strikingly faster. Overall, the remark-removal group is a worse group. These are grounds on which lenders would rightfully deny credit to the remark-removal group in the absence of the mandated remark removal. Yet even in this group, roughly only 25 percent has another remark after three years.

With simulations we find that the data best fits a proportion of 25-29 percent of the inherently bad type group, who obtain a remark with a probability equal to 0.125 in every period and the majority never receive one again. That is, it appears possible that only a minority of the remark-removal 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 remarks 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 remark removal is socially justifiable.

The rest of the paper is organized as follows, Section 2 outlines a short theory for consumers' loan application, Section 3 summarizes the relevant legislation, Section 4 describes the data, Section 5 takes a look at the short-run effect of remark removal, Section 6 the longer run, and Section 7 considers the existence of two subgroups within the remark-removal group. Section 8 summarizes and concludes.

2 Framework

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.

3 Credit remarks and legislation

In general, a credit remark 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 remarks are a decision by the national collection agency 'Kronefogden' or the cantonal courts that there is an order for payment;[2] the abuse of bank accounts, credit or mortgages; tax claims; debt reconstruction; and repossession and personal bankruptcy.

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.

[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.

4 Data description

The panel data employed for this article are a random sample 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 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

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

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 1,179 individuals for whom we can observe the removal of their credit remark; we call these panelists the *'remark-removal'* group. We define time 0 for each individual within the remark-removal group uniquely as the first time the remark dummy is observed to be equal to zero. The "remark-removal" indicator, D_{ct} , is set to one at t = 0 for this group. To be precise, at time 0, for a given borrower who has not had a new credit remark for a three-year period, the credit remark received at time -3 (measured in years) is removed. When this occurs, we place a one in the variable D_{ct}.

We construct a contrast group by identifying 14,130 individuals who had no remark on their credit records until the first of October 2001, a date picked to allow four subsequent years of observations.[6] So for everyone in the contrast group we define t equal zero at *'01 Oct. 2001'* and we set the "remark-removal" dummy S_c equal to zero. We realize that this extended period without remarks bears the risk of identifying a group that is exceptional 'good.' We address this in a robustness check, where we construct a contrast group more similar to the remark-removal group with the aid of propensity score matching; we find that the qualitative results are unaffected.

Descriptive statistics Table 1 illustrates the descriptive statistics on the credit scores for both the remark and contrast group in the whole period before the removal (t < 0), right before the removal (t = -1) and after the removal of their credit score

balance each month.

[6] To test we randomly picked other dates to function as time 0 for the contrast group, and we did not encounter significant changes in the estimation results.

(t > 0). As expected, individuals from the contrast group overall have a much better credit score than the individuals from the remark-removal group. There is only a slight overlap of the two distributions in the period before the remark removal. After the remark removal (at t = 0) the distribution of the remark-removal group makes a big shift toward better credit scores. For the contrast group there is no significant change before and after their fictional removal. In general, we will be using the credit scores at time t =-1 as a predictor of subsequent behavior, using the dummy variable D_{ct} in the short run to check if the remark-removal period is significantly different from the other time periods.

Table 2 describes the variables used in the regressions for the two groups and two periods. On average, the contrast group applies 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 Short-run effect of remark removal

When a credit remark 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 π_i.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 for three months afterwards to determine the empirical impact on the consumer's loan applications and the subsequent credit access in the short run.

Credit scores Let $Score_{c,t}$ be the credit score of individual c at time t. The period t change in credit scores is $Score_{c,t} - Score_{c,t-1}$. The empirical question is how large this change is at $t = 0$ when the credit remark is removed, and the "remove remark" dummy $D_{c,t}$ is set to one at $t = 0$, relative to other periods. We also investigate if the magnitude of this change is dependent on the initial level of the credit score. For this reason all panelists are sorted based on their initial credit score in every period from t=-12 to t=18 into five quantile ranges [0,20), [20, 40), [40, 60), [60, 80) and [80, 100).

The results are plotted as Figure 1a, which has the change in credit score on the vertical axes and time before and after remark removal at period S, event time where, $D_{ct} = 1$ and $t = 0$, on the horizontal axes. Each line shows the change for the score range in each period t. So individuals can fall into different score ranges over time.

The graph makes several points. First, there is a strong remark-removal effect at period t=0. All initial credit score ranges experience an abnormally large decline in credit score. Second, the effect appears to be strongest for initial scores in the ranges [20, 40) and [60,80).

We establish the statistical significance of these patterns by regressing score changes on period dummies, along with a time trend, within each initial score interval. The difference now is that panelists are sorted by quantile based on their credit score at t=-1, before the credit remark was removed.

We fit the fixed and time effect model only for the indiviuals in the remark-removal group,

$$Score_{c,t} - Score_{c,t-1} = b_0 + b_1 t + b_2 D_{c,t} + \varepsilon_c + e_{ct} \tag{1}$$

for each five ranges of credit scores separately. The results in Table 1 show a highly significant positive effect of remark removal on credit scores for all initial scores. Since low credit scores represent low default risks, a negative sign for the b_2 coefficients indicates an improvement in creditworthiness. We have thus shown the statistical significance of the results in figure 1. The remark removal delivers an immediate boost to apparent creditworthiness, as represented by credit-scores, with a decrease in the probability of default between 8 and 18 percentage points.

To get an indication of whether these improvements in credit scores are large enough for the consumer to move toward a credit score sufficiently low enough to be considered by a bank for a loan aproval we plot in Figure 1b the percentage of people who have a credit score lower than 9 percent. We choose this cut-off point based on Boyes et al. (1989) findings that applicants whose default probability exceeded 9 percent were generally associated with negative profits for the lender and on a cut-off point range of 6-9 percent that was suggested by personnel at the credit bureau. Obviously, this choice remains arbitrary and will only serve the purpose as a proxy for credit access, later on we will show actual credit access by consumers.

Figure 1b shows that before the credit remark removal there were already people with a credit score below 9 in the first range of scores [0,20), starting with 6 percent at two years before removal (t=-12) up to 31 percent in the period right before the credit remark removal. All the other score ranges have no one with a score lower than 9. Following the credit scores of the individuals in these groups after the remark removal shows that the reduction in credit score caused by the credit remark removal at period S is sufficient to lower the scores for everyone in the initial two best credit score ranges below 9. The second worst range [60,80) consists directly after remark removal of 85 percent people with a good score but this is quickly reduced to 48 percent after one year (t =6). The percentage of individuals with a good score in the initial worst score range [80, 100) remains zero percent after credit remark removal.

Loan applications after remark removal Do these improvements in credit scores motivate consumers to apply for new credit? We plot the number of loan applications for the same five credit score ranges over time in Figure 2a. The graph clearly shows that the score range for which we have found the strongest decline in credit scores at t=0, namely, [60, 80), also displays the largest increase in loan applications after the credit remark is removed. This increase seems to remain high on average up to almost three years after removal. The other initial score ranges also demonstrate an upward trend in their loan applications after credit remark removal. The increase in loan applications seems to start before the remark removal at t=0. There are several ways to explain this early onset of increased loan applications, but the most intuitive is that individuals might not be aware of the exact timing of their credit remark removal, since the credit bureau does not give notice of this event and the individuals received this remark three years ago. The recollection of this date might also be blurred by the fact that receipt of additional credit remarks will reset the three-year-removal clock back to zero.

To show that Figure 2a is not driven by a relatively small number individuals, we plot in Figure 2b the percentage of people who apply for credit. For example, right after the credit remark removal 34 percent of the individuals in the [60, 80) initial score range apply for a loan.

To establish again the statistical significance of these events, we run a fixed-effect model, adding a dummy $D_{c,t}$ to the earlier regressions in Table 4 to indicate the period of remark removal. (Later in this paper we will examine the long-run effects.) The results, collected in Table 5, show that at t=1, the two-month period immediately after the removal of the credit remarks, all categories except one, the worst, show a significant positive effect on loan applications.

New credit after remark removal These increased loan applications translate into new loans. Figure 3a illustrates the number of outstanding loans for all panelists over time. During the period that the panelists still have their credit remark ($t < 0$) the individuals in the best credit score range [0,20) have substantially more credit than the other four score ranges, as we would expect. As time progresses, existing loan contracts end and because obtaining new loans while having a credit remark is difficult at best, for these best-credit individuals, the number of outstanding loans follows a steady decline. They almost reach the level of the other score ranges right before the credit score removal. Then when the credit remark is removed at time t=0, the number of outstanding loans rises substantially, especially for the [60, 80) range, which is the most active in applying for new loans. After three years the number of outstanding loans for all credit score ranges has increased considerably. The best score range not only recovered from the earlier decline but has surpassed it.

Figure 3a shows the average number of outstanding loans received by panelists before and after credit remark removal, while Figure 3b shows changes. The figures confirm that the average number tends to remain constant or to fall before the remark removal, while after remark removal the average number rises substantially for all groups. The improvement in credit score and increased loan applications after the credit remark removal translate directly into significant new credit access.

Figure 3c gives the quantities of credit that these unsecured loans represent. It is useful to keep in mind that the average credit limit for the broad range of consumers without credit remarks (our comparison group) represented in our data set is roughly SEK 36,000 (~USD 5,000). However, the average hides a substantial variation, and the standard deviation is nearly SEK 90,000 (~USD 12,000).

Before credit remark removal, the average total credit limit for all but the very best credit score range is between SEK 10,000 and SEK 30,000. Three years after credit remark removal, the average total credit limit is between SEK 30,000 and SEK 60,000. Broadly speaking, credit access appears to have doubled.

Figure 3d shows that the average total saldo – total outstanding balance – before credit remark removal lies, for all but the best credit score ranges, around SEK 15,000-25,000 (~USD 2,000-3,250) and for the best score range it is around SEK 40,000-50,000 (~USD 5,200-6,500). After the credit remarks are removed, the average saldo for all ranges increases. In a pattern similar to that seen with the number of loans, the [60, 80) range increases the fastest.

In Table 6, we fit a similar fixed-effect model for the change in the number of outstanding loans, total limit and total saldo in panel A, B and C respectively. Since it takes time for a loan application to be granted, we use dummy variables for both the period of the remark removal, t=0, and the period afterward, t =1.

For all score ranges, there is no positive significant effect visible at t =0; indeed, the only significant effects are negative for the number of loans in panel A. These findings argue that there is a lag from the increase in loans applications to an increase in credit access. Two months later at t=1, there is, however, a significant positive effect for the three middle score ranges in the number of loans, saldo and limit. The best score range shows a significant change in the number of loans only at t=1. In panel A, the point estimates for the score ranges with a significant positive effect at t=1 are around one extra loan per 7 consumers, a bit less for the best borrowers, and no effect for the worst borrowers.

In panel B, the credit limit rises by more than SEK 8,600 (~USD 1,000) on average for the consumers in the second best score range two months after the credit remark removal. For the two score ranges that follow the second best, the rise in the limit is around SEK 4,000 on average. These results show that there is a boost in credit access for the majority of people only two months after the remark removal. However, for the [60 to 80) group, there is a (poorly estimated) large average decline in credit access in period t=0, which could offset the gain in period t=1.

6 Longer run effect of remark removal

The analysis shows that consumers whose credit remark 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.

We now study more precisely the longer run dynamics; to do so we will follow Musto (2004). We add to the 1179 panelists from the remark-removal group the whole contrast group of 14,130 panelists. The contrast group is contructed by identifying panelists who had no remark on their credit records until the first of October 2001, a date picked to allow four subsequent years of observations.[7],[8] So for everyone in the contrast group we define t equal zero at *'01 Oct. 2001'.* The dummy that indicates if the individual belongs to the remark-removal group, S_c is equal to one for all panelists within the remark-removal group, and zero for the others.

For each variable of interest we will run nine OLS regressions explaining expanding time periods,

$$Y_{c,t+n} - Y_{c,t-1} = b_0 + b_1 Score_{c,t=-1} + b_2 S_{ct} + b_3 Y_{c,t=-1} + \varepsilon_c \tag{2}$$

, n = [0, 3, 6,...,24] so the final regression considers the difference of the dependent variable over 24 periods, which is four years. We adjust for serial correlation by clustering the error terms on the individual level. The number of observations in the remark-removal group declines over time since the actual timing of the remark removal is not constant in the panel, see table 6 for an account of this decline. b_2 is the parameter of interest: the predicted change for consumers in the remark-removal group $S_{ct} = 1$.We control for the credit score, $Score_{c,t=-1}$,and for the value of the dependent variable $Y_{c,t=-1}$of the consumer at $t = -1$.

Credit scores in the longer run Table 7 presents the results of the nine regressions to show the longer run development of the credit score after the initial credit remark removal up to 24 periods. From the earlier analysis we expect a negative loading on the *loseremark* dummy S_{ct} in the first regression, reflecting the initial decline (improvement) in credit scores; the loading on the other eight *loseremark* dummies shows the longer run effect.

[7] To test we randomly picked other dates to function as time 0 for the contrast group, and we did not encounter significant changes in the estimation results.

[8] We realize that this extended period without remarks bears the risk of identifying a group that is exceptional 'good.' We address this in a robustness check, where we construct a contrast group more similar to the remark-removal group with the aid of propensity score matching; we find that the qualitative results are unaffected.

As expected the excess credit score change of the credit remark removal panelists from t=-1 to t=0 is negative. This improvement in apparent creditworthiness continues to be significant for 9 periods, one and a half years. Two years down the road, however, the excess reduction in credit scores is barely significant, and beyond two years the excess change remains negative but the confidence interval is wide. So the boost in creditworthiness delivered by the removal of the credit remark lasts up to two years. However, unlike Musto (2004), there is no evidence that credit scores become worse on average than they were prior to the credit remark removal.

Loan applications in the longer run To see how this long-term increased creditworthiness leads to more credit in the long run, we first examine the longer run dynamics of loan application. 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. Table 8 shows the regression results for a set of nine regressions for cumulative loan applications.

While controlling for the individuals initial $Score$ and number of *loan applications* at $t = -1$, we find a positive loading on loseremark as expected in the short run but this continues up to 21 periods. The peak lies around two and half years.[9]

[9] The *loanapplications* at t=-1 is subject to autocorrelation that fades as the horizon increases. This causes the R-squares to implode.

Increased applications appear to be made based on the improvement in credit score for a prolonged period.

New credit in the longer run To see if the loan applications were successful on average we look at the longer run results for the number, limit and saldo of the individuals' total unsecured outstanding loans in Tables 10, 11 and 12, respectively.

The loading on the *loseremark* dummy, which captures the impact for the individuals who have their remark removed, starts with a negative loading in the first period after the credit remark removal. This illustrates again, as was shown earlier in Table 3 for the short run, the lag between applying for a loan and obtaining one. After this initial decline, however, there remains a positive loading on the *loseremark* dummy for all three credit measures up to two and a half years. The loading for number of loans continues to be significantly positive for one more year after that, where the coefficient reaches its maximum after two years.

With an average of 1.35 loan applications arising in the two years ($t = 12$) after the removal of the credit remark shown in Table 8, in Table 10 we see an average of 0.63 new loans over the same period. Thus it would appear that nearly half of the loan applications were approved. However, these numbers may not be directly comparable. First, it may take a few months to approve an application. Second, note that the increase in the number of outstanding credits and loan amounts is a net amount, so the old credits may have been extinguished.

In Tables 11 and 12 we see the evolution of the limits and outstanding balances on the loans. Table 11 shows the total limits. Unlike the number of outstanding credits, the total limit impact of the remark removal reaches its maximum at 18 months, although the difference between that coefficient and the coefficient for 24 months is not statistically significant. The average increase is SEK 21,000, roughly the average amount suggested in Figure 3c. 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 remark is removed, and the boost lasts for three and half years.

Excess loan applications' effect on credit-scores in the longer run As mentioned in the framework section, inquiring for a loan bears a cost, namely it increases one's credit score (decreases creditworthiness). We have seen in Table 2 that, at least in the short run, credit remark removal induces new loan applications; therefore, we expect that some of the longer run decline in credit scores may be due to the availability of new credit.

Now that we have shown that the removal of individuals' credit remarks leads to an excess increase in loan applications that lasts for three and half years, we would like to capture the negative effect of this increase on the individuals' credit score separately. For this purpose we run the same regressions as shown in Table 7 with dependent variables $Score_{c,t=n} - Score_{c,t-1}$ controlling for the change in loan applications in the same period ($Loanappl_{c,t=n} - Loanappl_{c,t-1}$) and the interaction term of the loseremark dummy and the change in loan applications: $Loseremark * Loanapplication$. Table 9 presents the regression results. While the loading on $loseremark$ remains more or less the same as in Table 7, the loading on $Loanappl_{c,t=n} - Loanappl_{c,t-1}$is, as expected, significantly positive for the lion's share of the time period under consideration, which means a negative effect on creditworthiness. Only in the short run, when the excess change in loan applications was not that large (see Table 4) we see that the confidence interval is too wide. The loading on the interaction term that captures the effect of the excess loan application for those individuals who had their credit remark removed is positive, but only significant at a 10 percent level for the 9-18 time periods, one and a half to three years. So by this measure, the negative effect on credit scores due to excess loan applications does not undo the positive effect on credit scores for those individuals whose credit remark was removed.

6.1 Defaulting

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 down the road. To address this question we predict whether an individual has received again a credit remark after the date of the credit remark removal ($t > 0$).

The prediction model is a Probit model;

$$Default_{c,t=n} = b_0 + b_1 Score_{c,t=-1} + b_2 S_c + \varepsilon \tag{3}$$

where the dependent variable $Default_{c,t=n}$ is the dummy variable that is equal to one if the individual, c has a credit remark at time t, with $t > 0$. As before we consider a total of $n = 24$ periods. So the final estimation predicts default four years after remark removal. The explanatory variables are the $Credit\ Score$ at $t = -1$ and the parameter of interest is again b_2 the predicted value for the individuals in the remark-removal group ($S_c = 1$). We fit this model to the same sample used in the longer run regression above and report the results in Table 13.

As expected, the loadings on initial credit scores at t = -1 are significantly positive, since higher credit scores imply higher probability of default by construction. The influence of remark removal captured by b_2 predicts extra defaults from the first period after remark removal to one and a half years afterwards. In the following year, the model also predicts extra defaults but at a low significance level of 10 percent. In the final period we consider, four years, the loading turns negative, but the confidence interval is too wide for it to be a significant prediction.

Thus Table 13 shows a greater incidence of default among the remark-removal group.

6.1.1 Sensitivity analysis: the contrast group revisited

As explained earlier, for these longer run analyses we combine two samples: the *contrast* group and the *remark-removal* group. Within the analyses, the development of the contrast group over time than represents the 'regular' path, defined as a path followed by individuals who did not experience an exogenous credit remark removal within the window of the panel. When we write an 'excess' change in the variable of interest, we imply an excess change compared to what one's own credit score at t= -1 predicts, given the regular path of the contrast group. One assumes, in this case, that if the credit bureau makes efficient use of it's available information that the individuals' 'true' credit risk was captured by the credit score at t = -1, while the credit remark was still registered on one's credit report. The decrease caused by the exogenous removal of information is only a temporary deviation. The evaluation by the credit bureau of the individuals' credit risk will converge toward the true credit risk as new information becomes available over time.

The question is: what would be the appropriate 'regular' path for the credit remark-removal group had they not experienced this exogenous change? As a start, we will construct a new contrast group that is more similar to the individuals in the remark-removal group at the time at which they still had their credit remark, t=-1[10]

Propensity score In order to construct a new contrast group that is more similar to the individuals in the remark removal group at the time they still had their credit remark, t=-1 we will make use of propensity score matching. That is, we start with

[10] In the near future we want to explore the panalists for whom we observe the full credit remark cycle: before, while and after the exogenous removal of credit remarks. Given the size of the observation window of this panel, five years, and the time after which the mandatory removal is executed, three years, there are not many such panelists available: only 123. Nevertheless we believe there is a lot to be learned from this small group.

estimating a probit model[11]

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

where the dependent variable is the *Loseremark* dummy S_c, and the explanatory variables (the variables that we want the contrast group to be more similar to) 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 at t = -1. We fit the model to the sample that includes both the 'old' contrast group and the remark-removal group. We then use the individuals' propensity scores, which are simply the in-sample predicted probabilities that one will lose one's remark ($S_c = 1$), to find the common support. The common support is the range of propensity scores that occur both in the contrast group and in the remark-removal group. We select only those individuals from the old contrast group that fall within the common support range:1,849 panelists. We call this the 'new contrast' group. We will then run the same regression as in the longer run analyses and the results are presented in Tables 14, 15 and 16.

Longer run effects with the *'new contrast'* group We estimate the same model described by equation 2. for the longer run effects on credit scores and loan applications. For the longer run effects on defaults, we estimate the model described by equation 3, only this time we use the sample that consists of both the new 1,849 contrast group panelists and the unchanged 1,179 credit remark-removal panelists.

Let's start with the longer run dynamics of the credit scores. Overall the results are remarkably similar compared to the results with the original contrast group presented in Table 14. The only small difference is the lack of significance when the

[11] We make use of the program: psmatch2 within STATA in order to immediately get the propensity score for every individual and not have to make the in-sample predicted probabilites separately.

change in credit scores over two years are considered. The same is true for loan applications (Table 15); there remains a positive and significant loading on the loseremark indicator that lasts only half a year longer - for four years - than was the case with the original contrast group. Finally, the results for defaults are presented in Table 16. Of the three models we estimate, these results are affected the most by the use of the new (more similar) contrast group. Even though the results are never altered, the significance is reduced in all periods but period 6. What remains is a positive loading on the loseremark indicator, generally at a 5 percent level, lasting for two and a half years.

All in all, our results seem pretty robust against a change in the contrast group toward a more similar contrast group. In general, using the more similar contrast group seems to reduce significance in the last three periods and the excess increase in defaults has become less significant overall.

Heterogeneous effects for two groups of creditworthiness The final analysis is to see if the effects differ for better and worse panelists. To test this we sort the individuals from the total sample (the new contrast group and the remark- removal group combined) into two groups based on their propensity scores: the first half is the better group and the second half is the worse group. We can only split the group in two because we need enough panelists from the remark-removal group in both groups. Again, we estimate the three models for longer run effects of credit remark removal on credit scores, loan applications and defaults: The results are presented in Tables 17, 18 and 19.

Interestingly, the longer run effects on credit scores for the two groups turn out to be very different from each other. As the 'better' group follows the earlier obtained longer run effects, the worse group diverges. For the worse group there is no longer run effect of credit remark removal on credit scores. Only in the first period after the removal is there an excess decrease in credit scores for the loseremark panelist. The next period, half a year later, the loading is reversed: credit scores increase (a decline in creditworthiness), but it is insignificant.

The longer run effects on loan applications for the two groups differ to a lesser extent, but still vary significantly from each other. The loseremark panelists of the better group stop having significant excess loan applications after one and a half years, unlike the loseremark panelist from the worse group, who retain a positive and significant loading up to four years, which is more in line with our earlier findings.

Last, the longer run effects on defaults are presented in Table 19. These results.show that splitting up the sample leaves too little precision for all confidence intervals of the loseflag coefficients are too wide. Looking at the sign of the coefficients in general, there seems to be a split between the better and worse group. As expected the better group defaults less and the worse group defaults more compared to the contrast group.

7 Two subgroups

Unlike bankruptcies, credit remarks also include delinquencies that may arise out of forgetfulness, accident, and legal disputes, rather than the inability or unwillingness to repay debt. As a result, it is possible that the removal of this information may have a more ambiguous effect on outcomes. We therefore consider that the remark removal group consists of two subgroups: one that obtained a remark because its members are inherently bad types, and one that obtained a remark because of a random event or tremble, which will not be repeated. For example, a credit remark can be acquired because an individual fails to pay a utility bill while on vacation or because a payment is misdirected.

Figure 4 shows the proportion of individuals with a new credit remark in the remark-removal group, the contrast group and the new contrast group over time, starting from their credit remark removal at time S. The remark-removal group does acquire remarks strikingly faster. After one period, 3.56 percent of the remark-removal group have already received a remark, and after three periods, 8.52 percent. These are the grounds on which lenders would rightfully deny credit to the remark-removal group in the absence of the mandated remark removal. Yet, even in this group, roughly only 25 percent has another remark after three years. One interpretation is that the majority of individuals in this group experienced a tremble, which for a period of time made it difficult for them to acquire credit. Another, complementary interpretation (based on Elul and Gottardi, 2007, and Vercammen, 1995), is that individuals who have their remarks removed have a strong incentive to exert effort to pool with the good borrowers who are allowed credit. Under either interpretation, there appears to be some ground for belief that remark removal may be socially optimal.

Simulation If a proportion p were of the inherently bad type group, and these obtain a remark with a probability equal to ρ in every period, while the others will never obtain a remark again, then after n periods, the total expected number of types with remarks is equal to

$$p - p(1 - \rho)n$$

When n=1, this is equal to ρp.

What values of ρ and p best fit the data? A series of simulations were performed, and the results are shown in Table 20. We find that with a rho of 0.125, a p of 0.29 results in overprediction of credit remarks at all dates, while with a p of 0.25, an underprediction of credit remarks occurs at all dates. Thus if we assume a rho of 0.125, then it appears that the proportion of bad borrowers is between 0.29 and 0.25. That is, it appears possible that only a minority of the remark-removal group is inherently high risk.

8 Summary and Conclusions

Our first finding is that in the Swedish data, when credit remarks 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 1a
Change in credit scores
Before and after credit remark removal at period S_c

Note.-There are 1179 panelists from the remark-removal group who lose their credit remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1179, we set loseremark D_{ct} to 1 at t=0 defined to be the first month without the credit remark. Hence S_c, event time, differs among the panelists. Panelist are sorted according to their credit score in every period from t=-12 to t=18 into five ranges [0,20), [20, 40), [40, 60), [60, 80) and [80, 100).

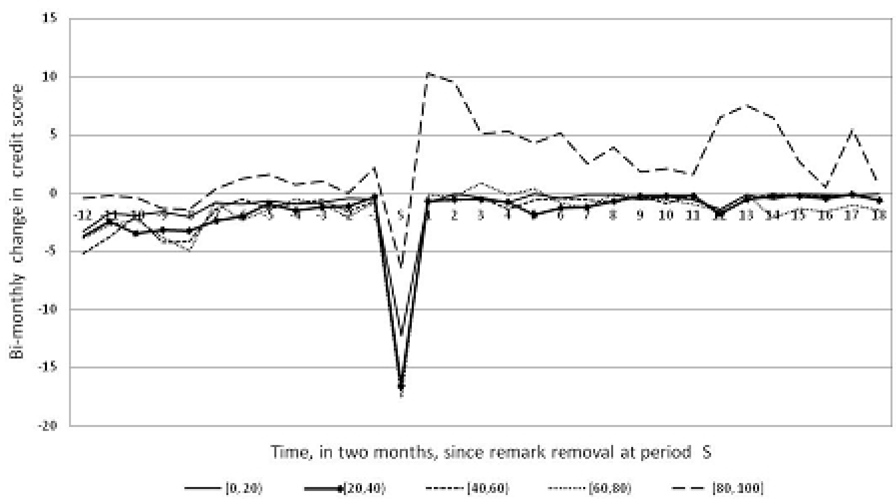

Figure 1b
Percentage of people with a *'good'* credit score
before and after credit remark removal at period S_c

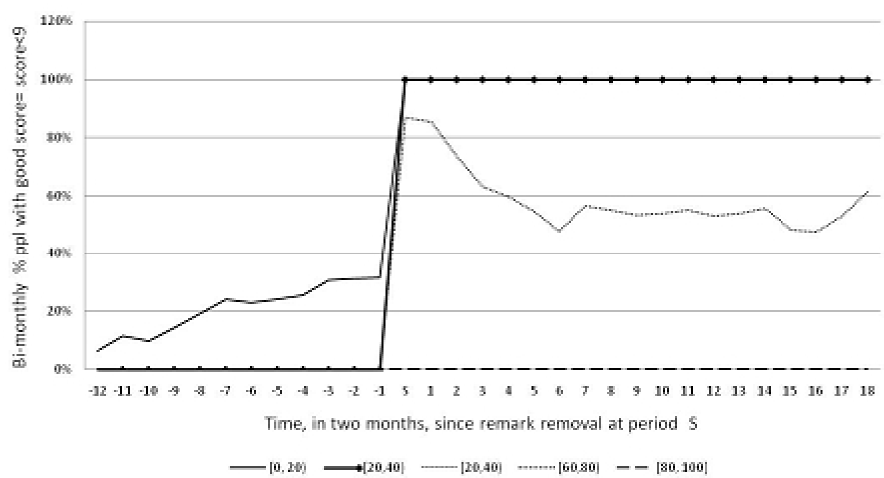

Figure 2a
Number of Loan Applications
Before and after credit remark removal at time S_c.

Note.-There are 1179 panelists from the remark-removal group who lose their credit remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1179, we set loseremark D_{ct} to 1 at t=0 defined to be the first month without the credit remark. Hence S_c, event time, differs among the panelists. Panelist are sorted according to their credit score in every period from t=-12 to t=18 into five ranges [0,20), [20, 40), [40, 60), [60, 80) and [80, 100).

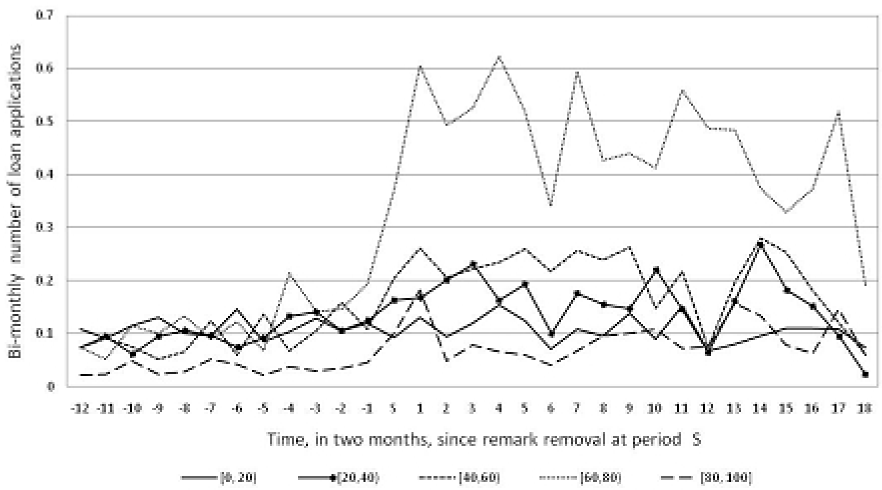

Figure 2b
Percentage of individuals who apply for a loan
Before and after credit remark removal at time S_c.

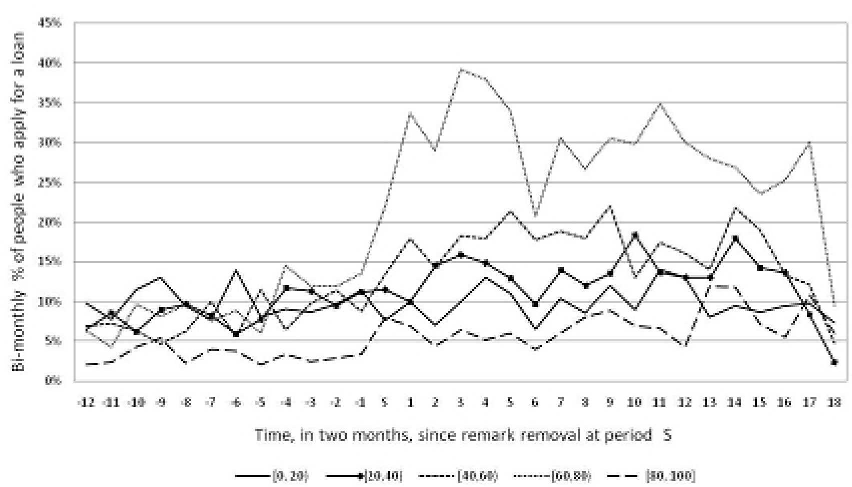

Figure 3a
Total number of outstanding loans
Before and after credit remark removal at time S_c.

Note.-There are 1179 panelists from the remark-removal group who lose their credit remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1179, we set loseremark D_{ct} to 1 at t=0 defined to be the first month without the credit remark. Hence S_c, event time, differs among the panelists. Panelist are sorted according to their credit score in every period from t=-12 to t=18 into five ranges [0,20), [20, 40), [40, 60), [60, 80) and [80, 100).

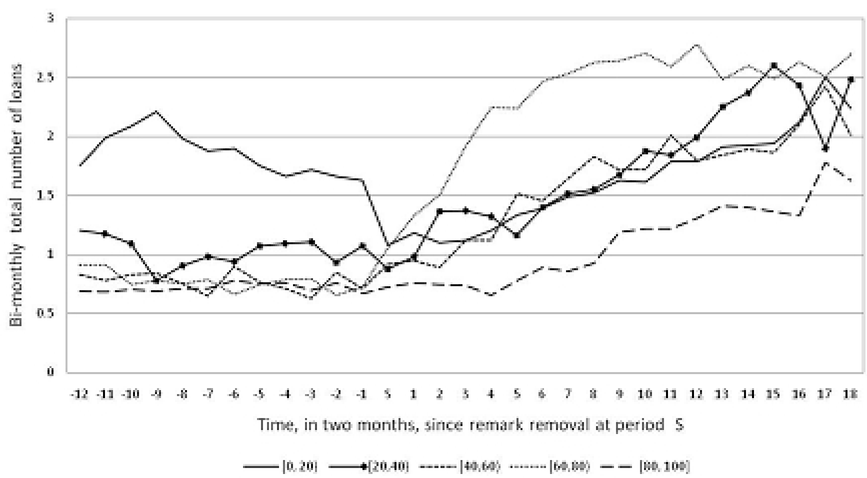

Figure 3b
Change in total number of outstanding loans
Before and after credit remark removal at time S_c.

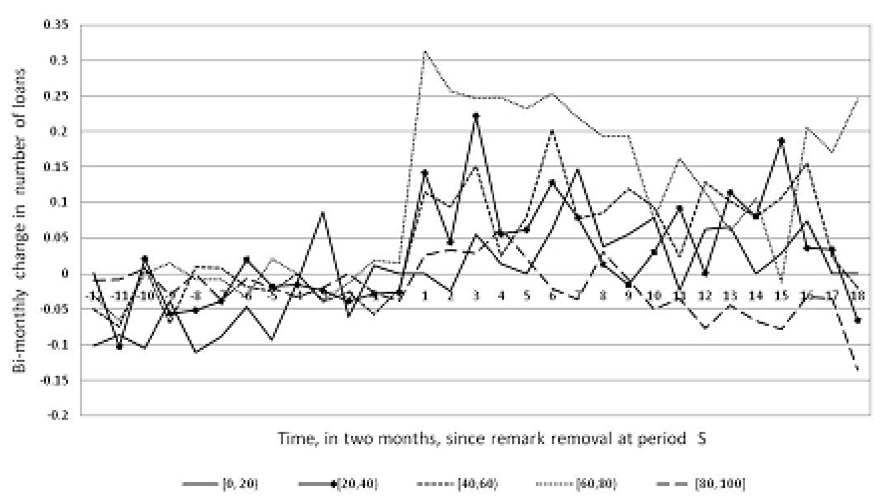

Figure 3c
Total limit in Swedish Kronor
Before and after credit remark removal at time S_c.

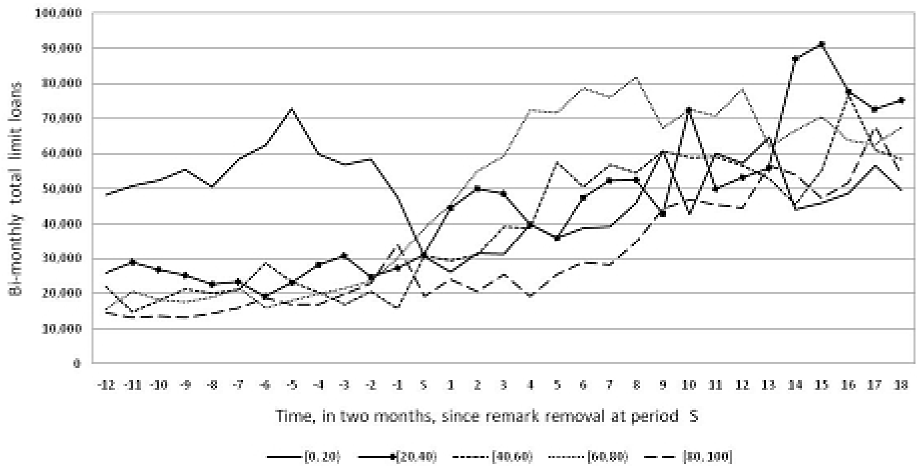

Figure 3d
Total outstanding balance in Swedish Kronor
before and after Credit-Remark removal at time S_c.

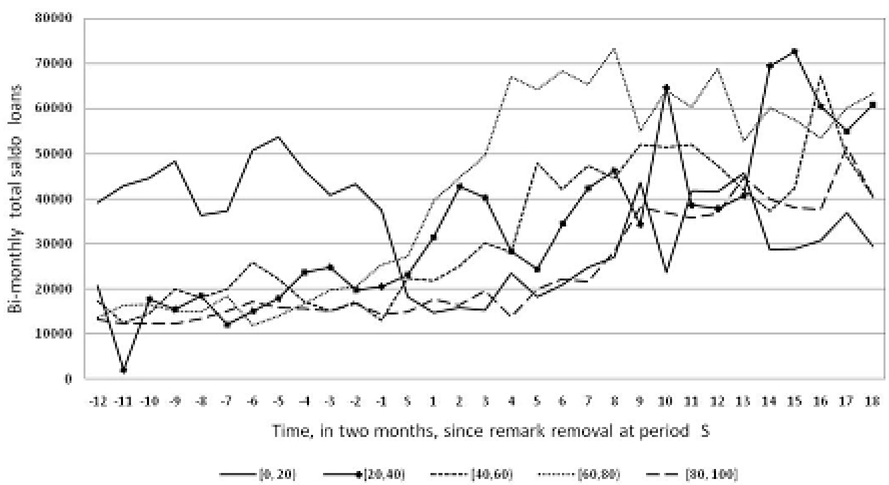

Figure 4
Percentage of individuals with a new credit remark
After credit remark removal at time S_c

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelist from the contrast group and new contrast group t= 0 to be defined as 01Oct2001 and Loseremark S_c is set to 0.

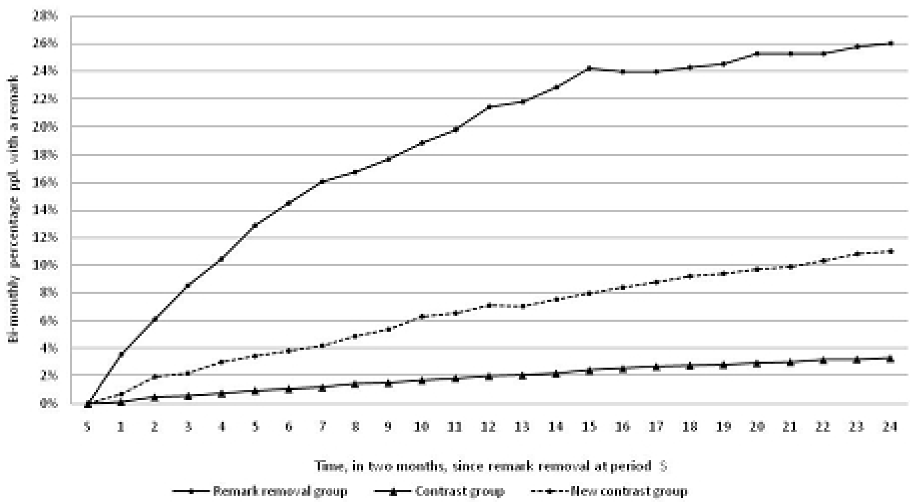

Table 1
Credit score distributions
Contrast group and remark-removal group
Before and after credit remark removal

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelist from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0.

Credit Score Distribution	t < 0		t = -1		t > 0	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
Contrast group						
0 to 5	127,907	91%	12,823	91%	323,162	91%
5 to 10	9,481	7%	932	7%	19,914	6%
10 to 20	2,318	2%	241	2%	4,004	1%
20 to 40	813	1%	92	1%	2,381	1%
40 to 60	291	0%	27	0%	865	0%
60 to 80	92	0%	12	0%	933	0%
80 to 100	32	0%	3	0%	1,991	1%
Total	140,934	100	14,130	100	353,250	100
Remark group						
0 to 5	303	1%	0	0%	11,458	60%
5 to 10	728	3%	74	6%	2,000	10%
10 to 20	5,728	26%	584	50%	867	5%
20 to 40	6,106	28%	300	25%	903	5%
40 to 60	1,757	8%	66	6%	875	5%
60 to 80	2,592	12%	82	7%	1,008	5%
80 to 100	4,828	22%	73	6%	2,079	11%
Total	22,042	100	1,179	100	19,190	100

Table 2
Descriptive statistics
Contrast group and remark-removal group
Before and after credit remark removal

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelist from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0.

	Mean	Std. error	Min	Max	Obs.
Contrast group					
t < 0					
credit score	2.37	0.01	0.15	86.20	140,934
loan applications	0.08	0.00	0.00	8.00	140,934
total no. credit	1.40	0.01	0.00	20.00	140,934
total_limit	31,079.83	212.65	0.00	6,084,999.00	140,934
total_saldo	22,417.04	189.39	0.00	3,500,000.00	140,934
t >= 0					
credit score	2.98	0.02	0.15	99.96	353,250
loan applications	0.09	0.00	0.00	12.00	353,250
total no. credit	1.69	0.00	0.00	19.00	353,250
total_limit	37,294.19	155.75	0.00	11,000,000.00	353,250
total_saldo	25,226.91	142.45	0.00	11,000,000.00	353,250
Remark removal group					
t < 0					
credit score	44.21	0.21	0.54	99.85	22,042
loan applications	0.09	0.00	0.00	8.00	22,042
total no. credit	1.10	0.01	0.00	13.00	22,042
total_limit	26,350.88	580.39	0.00	2,472,754.00	22,042
total_saldo	22,120.11	471.64	0.00	2,415,308.00	22,042
t >= 0					
credit score	20.09	0.23	0.15	99.92	19,190
loan applications	0.20	0.00	0.00	22.00	19,190
total no. credit	1.64	0.01	0.00	20.00	19,190
total_limit	46,563.99	752.78	0.00	3,490,279.00	19,190
total_saldo	39,023.71	723.62	0.00	3,490,279.00	19,190

Table 3

Credit remark removal effects on the absolute change in credit scores

Note.-There are 1179 panelists from the remark-removal group who lose their credit remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1179, we set loseremark D_{ct} to 1 and define t=0 to be the first month without the credit remark. Let $Score_{c,t}$ be the credit score of individual c out at time t. Panelists are sorted by their credit score in the period before their credit remark was removed; $t = -1$, into five ranges [0,20), [20, 40), [40, 60), [60, 80) and [80, 100). Each pair of rows in this table represents a fixed-effect regression of the form $Score_{c,t} - Score_{c,t-1} = b_0 + b_1 t_c + b_2 D_{c,t} + \varepsilon$, where b_0 is the intercept, b_1 is the time-trend, b_2 is the abnormal change for $D_{c,t} = 1, when\ t = 0$,given the time trend. t-values are below the coefficients in italics.

Credit-Score range at t =-1	Intercept	Time Trend	Remark removal	Number Obs *Individuals*
[0, 20)	-0.97 ***	0.03 ***	-8.49 ***	7,900
	-6.19	*3.03*	*-68.49*	*235*
[20, 40)	-1.48 ***	0.04 ***	-11.18 ***	7,569
	-8.72	*4.63*	*-31.68*	*223*
[40, 60)	-1.29 ***	0.04 ***	-13.95 ***	7,627
	-6.72	*3.58*	*-31.58*	*228*
[60, 80)	-1.25 ***	0.05 ***	-18.00 ***	8,607
	-5.56	*4.46*	*-30.89*	*258*
[80, 100]	0.15 ***	-0.02 ***	-14.96 ***	7,919
	0.78	*-2.01*	*-11.15*	*235*

Table 4
Short-run effects of credit remark removal on loan applications

Note.-There are 1179 panelists from the remark-removal group who lose their credit remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1179, we set loseremark D_{ct} to 1 and define t=0 to be the first month without the credit remark. Let $Score_{c,t}$ be the credit score of individual c out at time t. Panelists are sorted by their credit score in the period before their credit remark was removed; $t = -1$, into five ranges [0,20), [20, 40), [40, 60), [60, 80) and [80, 100). Each pair of rows in this table represents a fixed-effect regression of the form $Loanappl_{c,t} - Loanappl_{c,t-1} = b_0 + b_1 t_c + b_2 D_{c,t=0} + b_3 t_{c,1} + \varepsilon$, where $Loanappl_{c,t} - Loanappl_{c,t-1}$ is the change in the number of loan applications, b_0 is the intercept, b_1 is the time-trend rend, b_2 is the abnormal change for $D_{c,t} = 1, when\ t = 0$ given the time trend, similar b_3 for the next period after removal $t_c = 1$. (t-values are below the coefficients in italics)

Credit-Score range at t = -1	Intercept	Time Trend	Remark remove t=0	t=1	Number Obs *Individuals*
[0, 20)	0.07 ***	0.00 ***	0.02	0.15 ***	7,900
	3.46	*4.19*	*0.69*	*2.57*	*235*
[20, 40)	0.07 ***	0.00 ***	0.10	0.12 ***	7,569
	3.39	*3.71*	*1.93*	*2.67*	*223*
[40, 60)	0.04 *	0.00 ***	0.04	0.19 ***	7,627
	1.73	*5.52*	*1.17*	*3.75*	*228*
[60, 80)	0.06 ***	0.00 ***	0.12 ***	0.25 ***	8,607
	2.49	*4.38*	*3.02*	*3.64*	*258*
[80, 100]	0.13	0.00 ***	0.02	-0.01	7,919
	0.87	*3.38*	*0.78*	*-0.29*	*235*

Table 5
Short run effects of remark removal on new credit access

Note.-There are 1179 panelist from the remark-removal group who lose their credit remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1179, we set loseremark D_{ct} to 1 and define t=0 to be the first month without the credit remark. Let $Score_{c,t}$ be the credit score of individual c out at time t. Panelists are sorted by their credit score in the period before their credit remark was removed; $t=-1$, into five ranges [0,20), [20, 40), [40, 60), [60, 80) and [80, 100). Each pair of rows in this table represents a fixed-effect regression of the form $X_{c,t} - X_{c,t-1} = b_0 + b_1 t_c + b_2 t_{c,t=0} + b_3 t_{c,1} + \varepsilon$, where $X_{c,t} - X_{c,t-1}$ is the change in the number of loans in panel A, Limit; panel B and Balance in panel C., b_0 is the intercept, b_1 is the time-trend, b_2 is the abnormal change for $D_{c,t} = 1, when\ t = 0$ given the time-trend, similar b_3 for the next period after removal $t_c = 1$. (t-values are below the coefficients in italics)

Credit-Score range at t=-1	Intercept	Time Trend	Remark remove t=0	t=1	Number Obs *Individuals*
A. Total number of Loans					
[0, 20)	-0.06 ***	0.00 ***	-0.02	0.10 ***	7,900
	-4.75	*5.13*	*-0.77*	*2.41*	*235*
[20, 40)	-0.08 ***	0.00 ***	-0.04 **	0.15 ***	7,569
	-5.77	*6.24*	*-2.03*	*3.4*	*223*
[40, 60)	-0.09 ***	0.00 ***	-0.04 **	0.15 ***	7,627
	-5.65	*6.73*	*-2.22*	*4.01*	*228*
[60, 80)	-0.04 ***	0.00 ***	-0.03 **	0.16 ***	8,607
	-2.97	*4.41*	*-2.05*	*4.82*	*258*
[80, 100]	-0.03 ***	0.00 **	-0.01	-0.01	7,919
	-3.17	*2.40*	*-1.24*	*-0.56*	*235*
B. Total limit					
[0, 20)	-4562.02 *	271.74 ***	-1694.75	3339.72	7,900
	-1.83	*2.29*	*-1.04*	*1.29*	*235*
[20, 40)	2514.27 ***	124.76 ***	-780.35	8670.82 ***	7,569
	-3.59	*3.60*	*-0.55*	*3.03*	*223*
[40, 60)	-2407.97 *	164.25 **	-90.18	3562.58 **	7,627
	-1.83	*2.43*	*-0.07*	*1.96*	*228*
[60, 80)	-433.23	63.11 ***	-4922.24	4576.77 ***	8,607
	-0.77	*2.56*	*-1.35*	*2.90*	*258*
[80, 100]	-785.09	44.41 **	-521.84	302.31	7,919
	-1.65	*1.96*	*-1.58*	*0.40*	*235*
C. Total saldo					
[0, 20)	-2492.23	178.42	-1671.88	1897.26	7,900
	-1.07	*1.57*	*-1.07*	*0.80*	*235*
[20, 40)	-2047.41 ***	94.51 ***	-546.19	8290.27 ***	7,569
	-3.05	*2.82*	*-0.39*	*3.11*	*223*
[40, 60)	-1976.90	134.49 **	-439.37	3452.29 **	7,627
	-1.52	*2.01*	*-0.32*	*1.95*	*228*
[60, 80)	-270.90	47.56 **	-4644.81	3861.39 ***	8,607
	-0.51	*2.03*	*-1.38*	*2.51*	*258*
[80, 100]	-686.59	37.96	-455.57	258.20	7,919
	-1.50	*1.74*	*-1.37*	*0.35*	*235*

Table 6
Number of individuals in the contrast group and remark removal group After remark removal

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0.

period	Number of individuals		Loseremark
	contrast	remark remove	dummy
t = 0	14,130	1,179	7.7%
t = 1	14,130	1,152	7.5%
t = 2	14,130	1,129	7.4%
t = 3	14,130	1,092	7.2%
t = 4	14,130	1,050	6.9%
t = 5	14,130	1,003	6.6%
t = 6	14,130	986	6.5%
t = 7	14,130	960	6.4%
t = 8	14,130	936	6.2%
t = 9	14,130	900	6.0%
t = 10	14,130	869	5.8%
t = 11	14,130	829	5.5%
t = 12	14,130	799	5.4%
t = 13	14,130	634	4.3%
t = 14	14,130	634	4.3%
t = 15	14,130	632	4.3%
t = 16	14,130	630	4.3%
t = 17	14,130	412	2.8%
t = 18	14,130	412	2.8%
t = 19	14,130	412	2.8%
t = 20	14,130	411	2.8%
t = 21	14,130	411	2.8%
t = 22	14,130	410	2.8%
t = 23	14,130	227	1.6%
t = 24	14,130	132	0.9%

Table 7
Longer run credit scores

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t.Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $Score_{c,t=n} - Score_{c,t-1}$ is the change in score from period $t = -1$ to $t = n$.(t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score	Loseremark	R-squared	Number Obs.
		c, t = -1	*S c, t = 0*		*Individuals*
Score c,t= 0-Score c,t=-1	0.08 *	-0.09 ***	-11.21 ***	52.0%	534,996
	1.75	*-5.00*	*-30.31*		*15,309*
Score c, t=3-Score c,t=-1	0.41 ***	-0.17 ***	-5.57 ***	11.9%	532,088
	5.70	*-5.56*	*-6.99*		*15,221*
Score c, t=6-Score c,t=-1	0.81 ***	-0.24 ***	-2.55 ***	8.0%	528,498
	9.15	*-6.85*	*-2.64*		*15,115*
Score c, t=9-Score c,t=-1	1.01 ***	-0.23 ***	-3.03 ***	6.1%	525,520
	10.17	*-6.02*	*-2.85*		*15,029*
Score c, t=12-Score c,t=-1	1.23 ***	-0.28 ***	-2.03 *	5.7%	522,019
	11.35	*-6.48*	*-1.71*		*14,928*
Score c, t=15-Score c,t=-1	1.37 ***	-0.27 ***	-0.15	3.2%	516,184
	11.47	*-5.51*	*-0.10*		*14,761*
Score c, t=18-Score c,t=-1	1.51 ***	-0.24 ***	-1.05	2.1%	508,572
	11.71	*-4.38*	*-0.59*		*14,542*
Score c, t=21-Score c,t=-1	1.60 ***	-0.21 ***	-1.10	1.6%	508,537
	12.04	*-3.86*	*-0.61*		*14,541*
Score c, t=24-Score c,t=-1	1.40 ***	-0.11 *	-2.99	0.4%	498,785
	9.89	*-1.72*	*-0.91*		*14,262*

Table 8
Longer run loan applications

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t.Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $Loanappl._{c,t=n} - Loanappl._{c,t-1}$ is the change in loan applications from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score	Loseremark	Loan appl.	R-squared	Number Obs.
		c, t = -1	*S c, t = 0*	*c, t = -1*		*Individuals*
loan appl. c, t=0 - Loan appl. c, t=-1	0.00	0.00 ***	0.12 ***	-0.85 ***	91.9%	534,996
	-0.16	*-4.94*	*5.97*	*146.04*		*15,309*
loan appl. c, t=3 - Loan appl. c, t=-1	0.13 ***	-0.01 ***	0.61 ***	-0.62 ***	51.9%	532,088
	15.97	*-5.31*	*10.78*	*-44.97*		*15,221*
loan appl. c,t= 6 - Loan appl. c,t= -1	0.30 ***	-0.01 ***	0.95 ***	-0.13 ***	20.6%	528,498
	25.01	*-4.75*	*10.66*	*-21.90*		*15,115*
loan appl. c,t= 9 - Loan appl. c, t=-1	0.50 ***	-0.01 ***	1.28 ***	-0.24 ***	6.7%	525,520
	26.57	*-4.62*	*10.15*	*-8.03*		*15,029*
loan appl. c, t=12 - Loan appl. c, t=-1	0.70 ***	-0.01 ***	1.35 ***	-0.09 **	2.5%	522,019
	26.75	*-2.53*	*8.75*	*-2.07*		*14,928*
loan appl. c, t=15 - Loan appl. c, t=-1	0.84 ***	0.00	1.59 ***	0.02	2.3%	516,184
	26.62	*-0.85*	*8.22*	*0.31*		*14,761*
loan appl. c, t=18 - Loan appl. c,t= -1	1.04 ***	0.01	1.44 ***	0.14 **	1.9%	508,572
	27.40	*1.60*	*5.59*	*2.01*		*14,542*
loan appl. c, t=21 - Loan appl. c, t=-1	1.19 ***	0.01 **	1.57 ***	0.25 ***	3.0%	508,537
	26.21	*2.03*	*5.68*	*3.10*		*14,541*
loan appl. c, t=24 - Loan appl. c, t=-1	1.40 ***	0.03 ***	0.68	0.38 ***	3.5%	498,785
	26.24	*3.93*	*1.48*	*3.79*		*14,262*

Table 9

Longer run credit scores while controlling for change in loan applications

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t.Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $Score_{c,t=n} - Score_{c,t-1}$ is the change in score from period $t = -1$ to $t = n$, and $Loanappl._{c,t=n} - Loanappl._{c,t-1}$ is the change in loan applications from period $t = -1$ to $t = n$, $Loseremark * Loanapplication$ is the interaction term of the latter two. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score *c, t = -1*	Loseremark *S c, t = 0*	Loan appl. *c, t = n - c, t = -1*	Loseremark* Loan appl.	R-squared	Number Obs. *Individuals*
A. Ols regressions							
Score c, 0 -Score c,-1	0.04	-0.10 ***	-11.18 ***	-0.06	-0.11	52.2%	534,996
	0.70	*-4.89*	*-30.39*	*-0.77*	*-0.39*		*15,309*
Score c, 3 -Score c,-1	0.44 ***	-0.16 ***	-5.76 ***	0.20	-0.23	11.6%	532,088
	6.00	*-5.20*	*-7.15*	*1.33*	*-0.45*		*15,221*
Score c, 6 -Score c,-1	0.76 ***	-0.23 ***	-3.10 ***	0.41 ***	-0.42	8.0%	528,498
	8.59	*-6.44*	*-3.15*	*3.09*	*-1.12*		*15,115*
Score c, 9 -Score c,-1	0.75 ***	-0.22 ***	-4.04 ***	0.64 ***	0.73 *	6.9%	525,520
	7.00	*-5.59*	*-3.87*	*4.92*	*1.81*		*15,029*
Score c, 12 -Score c,-1	0.73 ***	-0.26 ***	-3.11 ***	0.70 ***	0.68 *	6.9%	522,019
	6.05	*-6.18*	*-2.67*	*6.05*	*1.78*		*14,928*
Score c, 15 -Score c,-1	0.74 ***	-0.26 ***	-1.49	0.70 ***	0.51	4.5%	516,184
	5.68	*-5.25*	*-1.05*	*7.00*	*1.34*		*14,761*
Score c, 18 -Score c,-1	0.81 ***	-0.24 ***	-2.15	0.59 ***	0.71 *	3.3%	508,572
	5.82	*-4.25*	*-1.24*	*7.35*	*1.75*		*14,542*
Score c, 21 -Score c,-1	0.73 ***	-0.22 ***	-2.13	0.62 ***	0.40	3.1%	508,537
	5.01	*-3.84*	*-1.20*	*7.74*	*1.03*		*14,541*
Score c, 24 -Score c,-1	0.64 ***	-0.12 *	-3.35	0.45 ***	0.07	0.2%	498,785
	4.30	*-1.79*	*-1.04*	*7.07*	*0.08*		*14,262*

Table 10

Longer run total number of outstanding credit

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $no\_credit_{c,t=n} - no\_credit._{c,t-1}$ is the change in the number of outstanding credits from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score *c, t = -1*	Loseremark *S c, t = 0*	Total no.Credit *c, t = -1*	R-squared	Number Obs. *individuals*
no. credit c, t =0 - no. credit. c, t =-1	0.03 ***	0.00	-0.04 ***	-0.02 ***	1.3%	534,996
	9.24	*0.97*	*-3.28*	*-7.93*		*15,309*
no. credit c, t =3 - no. credit. c, t =-1	0.08 ***	0.00 ***	0.32 ***	-0.05 ***	3.6%	532,088
	14.40	*-3.48*	*7.95*	*-11.57*		*15,221*
no. credit c,t = 6 - no. credit. c, t =-1	0.16 ***	0.00 ***	0.52 ***	-0.10 ***	6.9%	528,498
	21.39	*-2.34*	*8.85*	*-17.26*		*15,115*
no. credit c, t =9 - no. credit. c, t =-1	0.48 ***	-0.01 ***	0.58 ***	-0.10 ***	4.1%	525,520
	46.68	*-5.35*	*7.44*	*-14.31*		*15,029*
no. credit c, t =12 - no. credit. c, t =-1	0.56 ***	-0.01 ***	0.63 ***	-0.07 ***	2.2%	522,019
	48.66	*-5.26*	*7.16*	*-9.17*		*14,928*
no. credit c, t =15 - no. credit. c, t =-1	0.62 ***	0.00 ***	0.56 ***	-0.11 ***	3.2%	516,184
	48.75	*-2.18*	*5.70*	*-12.89*		*14,761*
no. credit c, t =18 - no. credit. c, t =-1	0.67 ***	0.00	0.46 ***	-0.11 ***	2.5%	508,572
	48.23	*0.43*	*3.48*	*-11.71*		*14,542*
no. credit c, t =21 - no. credit. c,t =-1	0.72 ***	0.00	0.39 ***	-0.10 ***	2.0%	508,537
	47.47	*0.80*	*2.96*	*-9.99*		*14,541*
no. credit c, t =24 - no. credit. c, t =-1	0.75 ***	0.01 ***	0.02	-0.12 ***	2.2%	498,785
	45.44	*2.83*	*0.06*	*-10.91*		*14,262*

Table 11
Longer run total limit of outstanding loans

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark S_c to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $total\_\lim it_{c,t=n} - total\_\lim it._{c,t-1}$ is the change in the limit of the outstanding credits from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score *c, t = -1*	Loseremark *S c, t = 0*	Total Limit *c, t = -1*	R-squared	Number Obs. *individuals*
total limit c, t =0 - total lim. c, t =-1	3369.22 ***	30.00	-2451.75 **	-0.11 **	6.2%	534,996
	2.69	*1.39*	*-2.31*	-2.35		*15,309*
total limit c,t =3 - total lim. c, t =-1	6780.92 ***	-80.04 *	10174.14 ***	-0.18 ***	8.1%	532,088
	3.77	*-1.84*	*4.88*	-2.69		*15,221*
total limit c, t =6 - total lim. c, t =-1	12393.00 ***	-110.67	14685.45 ***	-0.29 ***	3.7%	528,498
	6.77	*-1.64*	*4.35*	-4.79		*15,115*
total limit c, t =9 - total lim. c, t =-1	16631.14 ***	-247.87	24164.40 ***	-0.34 ***	4.9%	525,520
	8.88	*-2.44*	*4.10*	-5.55		*15,029*
total limit c, t =12 - total lim. c, t =-1	19276.56 ***	-161.06	20724.46 ***	-0.36 ***	14.4%	522,019
	12.50	*-1.79*	*4.90*	-6.06		*14,928*
total limit c, t =15 - total lim. c, t =-1	20588.60 ***	-37.82	18822.57 ***	-0.38 ***	12.5%	516,184
	13.37	*-0.35*	*3.41*	-6.49		*14,761*
total limit c, t =18 - total lim. c, t =-1	22438.26 ***	333.35 ***	8187.82	-0.41 ***	12.8%	508,572
	16.41	*2.80*	*1.48*	-7.85		*14,542*
total limit c, t =21 - total lim. c, t =-1	24828.44 ***	279.73 ***	8016.22	-0.40 ***	8.6%	508,537
	17.19	*2.35*	*1.38*	-8.00		*14,541*
total limit c, t =24 - total lim. c, t =-1	26382.37 ***	702.14 ***	-12096.66	-0.40 ***	7.5%	498,785
	18.85	*4.30*	*-1.22*	-7.90		*14,262*

Table 12

Longer run total outstanding balance

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $total\_saldo_{c,t=n} - total\_saldo_{c,t-1}$ is the change in total saldo of the outstanding loans from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score c, t = -1	Loseremark S c, t = 0	Total Saldo c, t = -1	R-squared	Number Obs. *Individuals*
total saldo c,t = 0 - total saldo c, t = -1	2554.25 ***	46.11 **	-2096.78 **	-0.13 **	7.1%	534,996
	2.63	*1.86*	*-2.04*	-2.31		*15,309*
total saldo c, t = 3 - total saldo c, t = -1	5238.16 ***	-55.13	9641.39 ***	-0.22 ***	9.5%	532,088
	3.81	*-1.13*	*4.88*	-2.72		*15,221*
total saldo c, t = 6 - total saldo c, t = -1	10233.60 ***	-56.61	13172.49 ***	-0.34 ***	4.4%	528,498
	7.06	*-0.82*	*3.99*	-5.23		*15,115*
total saldo c,t = 9 - total saldo c,t = -1	12695.73 ***	-160.91	22310.92 ***	-0.41 ***	6.0%	525,520
	8.29	*-1.55*	*3.81*	-5.82		*15,029*
total saldo c, t = 12 - total saldo c, t = -1	13529.36 ***	-58.81	19982.22 ***	-0.44 ***	19.6%	522,019
	11.67	*-0.65*	*4.86*	-6.71		*14,928*
total saldo c,t = 15 - total saldo c, t = -1	14199.48 ***	60.71	16663.19 ***	-0.45 ***	16.6%	516,184
	12.16	*0.55*	*3.11*	-6.94		*14,761*
total saldo c,t = 18 - total saldo c,t = -1	15570.07 ***	438.04 ***	5741.56	-0.50 ***	17.8%	508,572
	15.44	*3.85*	*1.14*	-9.11		*14,542*
total saldo c, t = 21 - total saldo c, t = -1	17165.00 ***	383.05 ***	5520.91	-0.50 ***	12.9%	508,537
	16.03	*3.41*	*1.02*	-9.44		*14,541*
total saldo c, t = 24 - total saldo c,t = -1	18220.88 ***	776.95 ***	-11941.81	-0.52 ***	13.0%	498,785
	17.58	*5.16*	*-1.31*	-10.39		*14,262*

Table 13
Longer run delinquency

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 14,130 panelists from the contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents a probit regression predicting delinquency for individual c, at time t, $Default_{c,t}$ (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score c, t = -1	Loseremark $S_{c,\, t=0}$	Pseudo R-squared	Number Obs. *individuals*
Default c, t= 1	-3.05 ***	0.02 ***	0.57 ***	23.7%	534,996
	-46.63	*7.18*	*3.64*		*15,309*
Default c, t= 3	-2.61 ***	0.02 ***	0.39 ***	21.8%	532,088
	-68.19	*12.05*	*3.59*		*15,221*
Default c, t=6	-2.40 ***	0.03 ***	0.46 ***	21.6%	528,498
	-78.53	*14.00*	*5.08*		*15,115*
Default c, t= 9	-2.28 ***	0.03 ***	0.39 ***	20.4%	525,520
	-84.05	*15.03*	*4.40*		*15,029*
Default c, t= 12	-2.18 ***	0.03 ***	0.37 ***	19.6%	522,019
	-88.01	*15.33*	*4.21*		*14,928*
Default c, t= 15	-2.11 ***	0.04 ***	0.32 ***	17.5%	516,184
	-88.99	*14.71*	*3.50*		*14,761*
Default c, t= 18	-2.06 ***	0.04 ***	0.18 *	14.1%	508,572
	-89.05	*13.69*	*1.67*		*14,542*
Default c, t= 21	-2.03 ***	0.04 ***	0.19 *	13.9%	508,537
	-89.30	*13.58*	*1.80*		*14,541*
Default c, t= 24	-2.03 ***	0.05 ***	-0.16	12.3%	498,785
	-85.23	*13.05*	*-0.83*		*14,262*

Table 14
Longer run credit scores with the new contrast group

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 1,849 panelists from the new contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $Score_{c,t=n} - Score_{c,t-1}$ is the change in score from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score *c, t = -1*	Loseremark *Sc, t = 0*	R-squared	Number Obs. *individuals*
Score c,t= 0 -Score c,t=-1	-0.39 **	-0.09 ***	-10.94 ***	40.0%	105,446
	-2.11	*-4.21*	*-30.58*		*3,027*
Score c, t=3 -Score c,t=-1	-0.70 **	-0.16 ***	-4.74 ***	8.1%	102,538
	-2.21	*-4.86*	*-5.89*		*2,939*
Score c, t=6 -Score c,t=-1	0.53	-0.25 ***	-2.06 **	7.2%	98,948
	1.36	*-6.50*	*-2.11*		*2,833*
Score c, t=9 -Score c,t=-1	1.50 ***	-0.26 ***	-2.79 ***	6.8%	95,970
	3.31	*-3.16*	*-2.58*		*2,747*
Score c, t=12 -Score c,t=-1	2.48 ***	-0.33 ***	-1.93	7.7%	92,469
	5.02	*-6.98*	*-1.61*		*2,646*
Score c, t=15 -Score c,t=-1	2.91 ***	-0.34 ***	0.14	5.4%	86,634
	5.40	*-6.25*	*1.46*		*2,479*
Score c, t=18 -Score c,t=-1	3.92 ***	-0.35 ***	-0.55	4.9%	79,022
	6.68	*-5.74*	*-0.31*		*2,260*
Score c, t=21 -Score c,t=-1	4.05 ***	-0.33 ***	-0.49	4.3%	78,987
	6.82	*-5.35*	*-0.27*		*2,259*
Score c, t=24 -Score c,t=-1	3.92 ***	-0.27 ***	-0.54	2.2%	69,270
	5.98	*-3.51*	*-0.16*		*1,981*

Table 15

Longer run loan applications with the new contrast group

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 1,849 panelists from the new contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $Loanappl._{c,t=n} - Loanappl._{c,t-1}$ is the change in loan applications from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score c, t=-1	Loseremark S c, t=0	Loan appl. c, t=-1	R-squared	Number Obs. *individuals*
loan appl. c, t=0 - Loan appl. c, t=-1	-0.08 ***	0.00 **	0.16 ***	-0.84 ***	93.2%	105,446
	-6.06	*-2.31*	*6.89*	*-89.70*		*3,027*
loan appl. c, t=3 - Loan appl. c, t=-1	0.04	-0.01 ***	0.66 ***	-0.57 ***	53.5%	102,538
	1.22	*-5.14*	*10.86*	*-25.54*		*2,939*
loan appl. c,t= 6 - Loan appl. c,t= -1	0.28 ***	-0.01 ***	0.99 ***	-0.38 ***	23.4%	98,948
	4.65	*-5.78*	*10.21*	*-9.54*		*2,833*
loan appl. c,t= 9 - Loan appl. c, t=-1	0.61 ***	-0.02 ***	1.30 ***	-0.23 ***	10.4%	95,970
	6.57	*-6.91*	*9.46*	*-3.70*		*2,747*
loan appl. c, t=12 - Loan appl. c, t=-1	0.93 ***	-0.02 ***	1.36 ***	*-0.12*	5.2%	92,469
	7.56	*-5.20*	*8.13*	*-1.24*		*2,646*
loan appl. c, t=15 - Loan appl. c, t=-1	1.17 ***	-0.01 ***	1.61 ***	*-0.05*	4.6%	86,634
	8.12	*-3.80*	*7.77*	*-0.54*		*2,479*
loan appl. c, t=18 - Loan appl. c,t= -1	1.57 ***	-0.01 *	1.48 ***	*-0.01*	2.4%	79,022
	5.45	*-1.92*	*5.45*	*-0.05*		*2,260*
loan appl. c, t=21 - Loan appl. c, t=-1	1.82 ***	-0.01	1.61 ***	0.08	2.3%	78,987
	9.42	*-1.58*	*5.47*	*0.56*		*2,259*
loan appl. c, t=24 - Loan appl. c, t=-1	2.20 ***	0.00	1.04 **	0.13	0.9%	69,270
	9.93	*0.11*	*2.21*	*0.82*		*1,981*

Table 16

Longer run delinquency with the new contrast group

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 1,849 panelists from the new contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents a Probit regression predicting delinquency. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score *c, t = -1*	Loseremark *$S_{c, t=0}$*	Pseudo R-squared	Number Obs *individuals*
Default c, t= 1	-2.65 ***	0.02 ***	0.27 *	13.6%	105,446
	-26.12	*6.79*	*1.80*		*3,027*
Default c, t= 3	-2.26 ***	0.02 ***	0.17 **	16.0%	102,538
	-32.98	*10.97*	*2.14*		*2,939*
Default c, t=6	-2.02 ***	0.02 ***	0.24 ***	16.2%	98,948
	-35.39	*12.34*	*2.69*		*2,833*
Default c, t= 9	-1.87 ***	0.02 ***	0.18 **	15.9%	95,970
	-36.15	*12.99*	*2.09*		*2,747*
Default c, t= 12	-1.74 ***	0.03 ***	0.17 **	15.4%	92,469
	-36.19	*13.07*	*2.06*		*2,646*
Default c, t= 15	-1.69 ***	0.03 ***	0.18 **	15.2%	86,634
	-35.21	*12.37*	*2.15*		*2,479*
Default c, t= 18	-1.61 ***	0.03 ***	0.11	12.3%	79,022
	-34.18	*10.97*	*1.16*		*2,260*
Default c, t= 21	-1.56 ***	0.03 ***	0.12	12.1%	78,987
	-33.67	*10.86*	*1.32*		*2,259*
Default c, t= 24	-1.55 ***	0.03 ***	0.02	11.1%	69,270
	-31.27	*9.87*	*0.16*		*1,981*

Table 17
Longer run credit scores with the new contrast group
Two groups of creditworthiness

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 1,849 panelists from the new contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t.Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $Score_{c,t=n} - Score_{c,t-1}$ is the change in score from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score	Loseremark	R-squared	Number Obs.
		c, t = -1	S c, t = 0		*Individuals*
A. Better					
Score c,t=0 -Score c,t=-1	0.69 ***	-0.23 ***	-7.05 ***	42.5%	52,892
	4.28	*-7.59*	*-25.83*		*1,513*
Score c, t=3 -Score c,t=-1	0.99 *	-0.29 ***	-4.00 ***	4.0%	52,822
	1.88	*-2.94*	*3.87*		*1,511*
Score c, t=6 -Score c,t=-1	1.15 *	-0.26 **	-3.54 ***	2.0%	52,736
	1.90	*-2.24*	*-2.99*		*1,508*
Score c, t=9 -Score c,t=-1	0.37	0.03	-3.77 **	0.4%	52,701
	0.45	*0.20*	*-2.03*		*1,507*
Score c, t=12 -Score c,t=-1	-0.14	0.18	-6.22 ***	0.8%	52,596
	-0.15	*1.01*	*-3.28*		*1,504*
Score c, t=15 -Score c,t=-1	0.41	0.13	-5.11 **	0.4%	52,456
	0.44	*0.73*	*-2.16*		*1,500*
Score c, t=18 -Score c,t=-1	-0.57	0.42 **	-7.44 ***	0.9%	52,176
	-0.57	*2.11*	*-2.60*		*1,492*
Score c, t=21 -Score c,t=-1	-0.50	0.47 **	-9.17 ***	1.2%	52,176
	-0.51	*2.43*	*-3.52*		*1,492*
Score c, t=24 -Score c,t=-1	-1.03	0.61 ***	-13.83 ***	1.3%	51,651
	-1.00	*2.97*	*-5.71*		*1,477*
B. Worse					
Score c,t=0 -Score c,t=-1	-3.86 ***	-0.49 *	-9.30 ***	9.1%	52,554
	-3.81	*-1.94*	*-10.69*		*1,514*
Score c, t=3 -Score c,t=-1	-10.11 ***	-0.08 **	2.28	0.9%	49,716
	-5.85	*-2.36*	*1.32*		*1,428*
Score c, t=6 -Score c,t=-1	-5.47 ***	-0.21 ***	2.85	3.2%	46,212
	-2.53	*-4.74*	*1.35*		*1,325*
Score c, t=9 -Score c,t=-1	-4.30	-0.22 ***	1.51	3.2%	43,269
	-1.89	*-4.53*	*0.68*		*1,240*
Score c, t=12 -Score c,t=-1	-0.39	-0.33 ***	1.08	5.8%	39,873
	-0.16	*-5.92*	*0.47*		*1,142*
Score c, t=15 -Score c,t=-1	1.52	-0.35 ***	2.52	5.5%	34,178
	0.57	*-5.43*	*0.98*		*979*
Score c, t=18 -Score c,t=-1	6.02 **	-0.43 ***	0.18	7.0%	26,846
	1.98	*-5.61*	*0.06*		*768*
Score c, t=21 -Score c,t=-1	4.86	-0.40 ***	1.55	6.0%	26,811
	1.66	*-5.22*	*0.54*		*767*
Score c, t=24 -Score c,t=-1	4.56	-0.35 ***	1.93	3.7%	17,619
	1.27	*-3.27*	*0.50*		*504*

Table 18
Longer run loan applications with the new contrast group
Two groups of creditworthiness

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the1,849 panelists from the new contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents an OLS regression predicting score changes with the standard errors adjusted for clusters in individuals. $Loanappl._{c,t=n} - Loanappl._{c,t-1}$ is the change in loan applications from period $t = -1$ to $t = n$. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score	Loseremark	Loan appl.	R-squared	Number Obs.
		c, t = -1	Sc, t = 0	c, t = -1		*Individuals*
A. Better						
loan appl. c, t=0 - Loan appl. c, t=-1	0.00	-0.01 **	0.16 ***	-0.87 ***	93.4%	52,892
	-0.14	*-2.01*	*3.36*	*-68.92*		*1,513*
loan appl. c, t=3 - Loan appl. c, t=-1	0.05	0.02 **	0.51 ***	-0.68 ***	59.8%	52,822
	1.09	*2.10*	*3.92*	*-26.10*		*1,511*
loan appl. c,t=6 - Loan appl. c,t= -1	0.21 ***	0.03 **	0.89 ***	-0.50 ***	26.9%	52,736
	3.18	*2.11*	*3.87*	*12.58*		*1,508*
loan appl. c,t=9 - Loan appl. c, t=-1	0.32 ***	0.05 ***	1.04 ***	-0.33 ***	10.2%	52,701
	3.73	*3.00*	*3.25*	*-6.46*		*1,507*
loan appl. c, t=12 - Loan appl. c, t=-1	0.51 ***	0.07 ***	1.02 ***	-0.18 ***	3.9%	52,596
	4.86	*3.24*	*2.65*	*-3.03*		*1,504*
loan appl. c, t=15 - Loan appl. c, t=-1	0.55 ***	0.09 ***	1.37 ***	-0.05	3.8%	52,456
	4.58	*3.67*	*3.06*	*-0.69*		*1,500*
loan appl. c, t=18 - Loan appl. c,t=-1	0.68 ***	0.12 ***	0.88	0.03	3.5%	52,176
	4.77	*5.09*	*1.65*	*0.46*		*1,492*
loan appl. c, t=21 - Loan appl. c, t=-1	0.76 ***	0.15 ***	1.00	0.15	3.3%	52,176
	4.81	*5.27*	*1.03*	*0.90*		*1,492*
loan appl. c, t=24 - Loan appl. c, t=-1	0.93 ***	0.20 ***	0.04	0.24	3.6%	51,651
	5.31	*5.84*	*0.00*	*0.84*		*1,477*
B. Worse						
loan appl. c, t=0 - Loan appl. c, t=-1	-0.12 ***	0.00	0.17 ***	-0.81 ***	93.1%	52,554
	-2.75	*-1.25*	*4.07*	*-47.80*		*1,514*
loan appl. c, t=3 - Loan appl. c, t=-1	-0.05	0.00 ***	0.67 ***	-0.48 ***	44.8%	49,716
	-0.41	*-4.27*	*6.70*	*-10.12*		*1,428*
loan appl. c,t=6 - Loan appl. c,t= -1	0.32	-0.01 ***	0.88 ***	-0.30 ***	16.8%	46,212
	1.63	*-5.21*	*5.95*	*-3.02*		*1,325*
loan appl. c,t=9 - Loan appl. c, t=-1	0.91 ***	-0.19 ***	1.06 ***	-0.20	8.4%	43,269
	3.47	*-7.21*	*5.43*	*-1.49*		*1,240*
loan appl. c, t=12 - Loan appl. c, t=-1	1.39 ***	-0.02 ***	1.08 ***	-0.14	5.5%	39,873
	4.40	*-5.90*	*4.57*	*-0.89*		*1,142*
loan appl. c, t=15 - Loan appl. c, t=-1	1.90 ***	-0.02 ***	1.21 ***	-0.18	6.0%	34,178
	5.78	*-5.01*	*4.38*	*-1.19*		*979*
loan appl. c, t=18 - Loan appl. c,t=-1	2.50 ***	-0.28 ***	1.14 ***	-0.22	6.4%	26,846
	7.22	*-4.01*	*3.39*	*-1.66*		*768*
loan appl. c, t=21 - Loan appl. c, t=-1	2.84 ***	-0.03 ***	1.24 ***	-0.21	5.7%	26,811
	7.29	*-3.50*	*3.39*	*-1.43*		*767*
loan appl. c, t=24 - Loan appl. c, t=-1	3.72 ***	-0.03 ***	0.90 *	-0.27	8.3%	17,619
	8.40	*-3.39*	*1.82*	*-1.92*		*504*

Table 19
Longer run delinquency with the new contrast group
Two groups of creditworthiness

Note.- There are 1179 panelists from the remark-removal group who lose their remark between 01Feb2000 and 01Oct 2005. For panelist c of these 1,179, we set loseremark $S_c$to 1 and define t=0 to be the first month without the credit remark. For the 1,849 panelists from the new contrast group t= 0 (a fictional removal) is defined as 01Oct2001 and Loseremark S_c is set to 0. For any panelists $Score_{c,t}$ is the credit score of individual c at time t. Each pair of rows in this table represents a Probit regression predicting delinquency. (t-values are below the coefficients in italics)

Dependent Variable	Intercept	Credit Score $_{c,\,t=-1}$	Loseremark $S_{c,\,t=0}$	Pseudo R-squared	Number Obs. *Individuals*
A. Better					
Default c, t= 1	-3.13 ***	0.06 ***	-0.27	4.2%	52,892
	-11.14	*2.39*	*-0.81*		*1,513*
Default c, t= 3	-2.72 ***	0.07 ***	-0.33	6.5%	52,822
	-19.18	*4.88*	*-1.21*		*1,511*
Default c, t=6	-2.48 ***	0.08 ***	-0.16	6.6%	52,736
	-20.45	*5.57*	*-0.74*		*1,508*
Default c, t= 9	-2.30 ***	0.08 ***	-0.02	7.3%	52,701
	-22.03	*6.39*	*-0.10*		*1,507*
Default c, t= 12	-2.27 ***	0.10 ***	-0.21	8.1%	52,596
	-23.67	*8.33*	*-1.11*		*1,504*
Default c, t= 15	-2.11 ***	0.08 ***	-0.19	6.5%	52,456
	-23.30	*7.64*	*-1.00*		*1,500*
Default c, t= 18	-2.10 ***	0.09 ***	-0.35	7.3%	52,176
	-23.16	*8.36*	*-1.50*		*1,492*
Default c, t= 21	-2.04 ***	0.09 ***	-0.35	7.3%	52,176
	-23.33	*8.52*	*-1.58*		*1,492*
Omitted because no variation in loseflag					
B. Worse					
Default c, t= 1	-2.24 ***	0.01 ***	0.01	6.2%	52,554
	-11.63	*5.13*	*0.05*		*1,514*
Default c, t= 3	-1.95 ***	0.02 ***	0.00	9.7%	49,716
	-13.32	*8.64*	*0.01*		*1,428*
Default c, t=6	-1.56 ***	0.02 ***	0.03	9.2%	46,212
	-12.64	*9.42*	*0.24*		*1,325*
Default c, t= 9	-1.57 ***	0.02 ***	-0.02	11.0%	43,269
	-12.15	*10.33*	*-0.17*		*1,240*
Default c, t= 12	-1.45 ***	0.02 ***	0.02	10.6%	39,873
	-11.90	*9.99*	*0.19*		*1,142*
Default c, t= 15	-1.41 ***	0.02 ***	0.07	10.7%	34,178
	-11.10	*9.13*	*0.58*		*979*
Default c, t= 18	-1.20 ***	0.02 ***	-0.11	7.9%	26,846
	-9.25	*7.02*	*-0.92*		*768*
Default c, t= 21	-1.22 ***	0.02 ***	0.03	8.2%	26,811
	-9.43	*7.07*	*0.26*		*767*
Default c, t= 24	-1.25 ***	0.02 ***	0.07	8.5%	17,619
	-7.99	*5.49*	*0.45*		*504*

Table 20
Simulation results for values of p and ρ

A proportion p were of the inherently bad type group, and these obtain a remark with a probability equal to ρ in every period, t, while the others will never obtain a remark again.

Data			Simulation	
time, t	Number of observ.	proportion with remark	rho= .125 p= .29	rho= .125 p= .25
1	1152	0.036	0.036	0.031
2	1129	0.061	0.068	0.059
3	1092	0.085	0.096	0.083
4	1050	0.105	0.120	0.103
5	1003	0.129	0.141	0.122
6	986	0.145	0.160	0.138
9	900	0.177	0.203	0.175
12	799	0.214	0.232	0.200
15	632	0.242	0.251	0.216
18	412	0.243	0.264	0.227