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# Do Forbearance Plans Help Mitigate Credit Card Losses?

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**Abstract** In this paper, we examine how reinstated (i.e., *re-aged*) credit card accounts are likely to default again. Our sample data reveal that about 22% of the *re-aged* accounts default again, mostly in the first 24 months after reinstatement. We also find that a FICO score (public information) is a better predictor of a second default, while a payment behavioral score (private information) is a better predictor of a first default. Furthermore, the average FICO score of the 78% of the re-aged borrowers who did not default again rises about 20 points, an improvement in their relative risk profile overall. These findings suggest that the re-aging program provides a second chance for liquidity-constrained borrowers who would have otherwise defaulted on their debt.

**Keywords** Credit card default · Forbearance · Loss mitigation · Hazard models

## Introduction

After cash and checks, credit cards serve as the third most popular means of payment for millions of routine transactions (Gross and Souleles 2002). With an automatic record-keeping and an interest-free grace period for settling accounts, they have become the

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primary source of safe, convenient and unsecured open-end revolving credit (Canner and Luckett 1992). During the last three decades, the volume of credit card debt increased twelve fold. For example, credit card debt has increased from $119 billion at year-end 1968 to $1.456 trillion in June 2000 (Darkin 2000), with credit card charge-offs rising as sharply.

In 1970, about 20% of US credit card holders held credit card debt after their most recent payment. By 1998, about 40% held credit card debt. According to the Survey of Consumer Finance, almost three-fourths of all US households had one or more credit card(s) in 1998, as compared to half of all households in 1970. Bank-issued credit cards account for much of the increased use of credit card debt during the last decade. Retail store card usage peaked a decade ago.

With the substantial rise in credit card debt, secondary market agencies as well as other investors and insurers of credit card securities are now actively trying to reduce losses associated with credit card delinquencies. Lenders are trying to mitigate losses associated with defaults by employing forbearance options such as lengthening repayment terms and lowering interest rates to help mitigate credit card losses and avoid charge-offs. Moreover, they also permit a credit card holder to reinstate their 90 days delinquent status, provided the borrower makes a minimum payment toward their debt. The *re-aging* of defaulted credit card account to current status effectively extends additional credit to borrowers by permitting them to maintain the original credit limit and interest rates, provided that the borrowers have good credit standing with the financial institution. The *re-aging* program is discussed in detail in the next section.

Thus far, empirical research modeling the determinants of credit card defaults and charge-offs (e.g., Gross and Souleles 2002; Agarwal and Liu 2003; Agarwal et al. 2003) did not distinguish between the first and second default.[1] This study contributes to the current literature by attempting to better understand the propensity of re-aged credit card accounts to stay current or default again.

Looking at mortgage debts, Ambrose and Capone (2000) found that subsequent default risk for reinstated borrowers was significantly higher than the risk of defaulting the first time. Interestingly, they also found that interest rates and time influenced second default in an opposite manner to first default. We followed the Ambrose and Capone (2000) approach and estimated a hazard function of credit card default for the first time as well as, conditional on reinstatement, for the second time. To this end, we used a unique and proprietary dataset of credit card accounts that were originated between January 1995 and December 1998, with performance information through December 2001. The dataset contains a panel of 241,452 individual credit card accounts that includes performance information of borrowers, credit risk scores (FICO and proprietary behavior scores), payment history, delinquency status, and most importantly a re-age indicator.

Our sample indicates that on average 78% of re-aged accounts stay current on their credit card payments, while 22% ultimately default a second time. Moreover, we also find that risk factors predicting a first default differ from those predicting a second default. FICO score (public information) is a better predictor of second default, while an internal payment behavioral score (private information) is a better predictor of first default. Given that a FICO score captures the relative credit risk profile of a borrower overall, including the risk on other outstanding credits after re-aging, it is reasonable that a FICO score is a better predictor of a second default. An internal payment behavioral score, on the other

[1] A default is defined as a credit card 90 days past due on the monthly payments; whereas, a charge-off is defined as a credit card balance written-off as uncollectible net of recoveries.

hand, may not fully capture the relative credit risk profile overall once an account is re-aged. Further analysis also shows that average FICO scores for the 78% of re-aged consumers who did not subsequently default the second time rises by as much as 20 points after their account was reinstated, indicating an improvement in their overall risk profile. These findings suggest that the re-aging program does provide a second chance for liquidity-constrained consumers who would have otherwise defaulted on their debt.

Our findings have some important implications for lenders, consumers, and investors in credit card securities. Lenders managing post default payment performance of re-aged credit card accounts must anticipate additional defaults and corresponding losses when gauging the potential success and failure of the program. Lenders can use these results to encourage account specific re-aging programs since a large portion of the accounts do cure and in turn, can avoid charge-off, providing significant savings to the lender. Additionally, the lenders should rely on public information in managing re-aged accounts as opposed to private information. Re-aging programs provide consumers an opportunity for a fresh start. Finally, investors can adjust the price of card-backed securities if they know that, for example, 2% of all accounts are re-aged and 22% of these re-aged accounts default again.

The structure of the rest of the paper is as follows. Section 2 provides a brief review of the institutional background of the credit card industry specifically focusing on the re-aging programs and the credit card default literature. Section 3 provides a brief description of the data and the proportional hazard methodology with time varying covariates of first and second default. Section 4 discusses the empirical findings, and Sect. 5 offers concluding remarks.

## Institutional Background: The Re-aging Program

In response to growing pressures from secondary market agencies and investors, lenders have been actively engaged in credit card loss mitigation programs. Proper loss mitigation programs are governed under strict rules laid out by Federal Financial Institutions Examination Council (FFIEC). According to the FFIEC, financial institutions should properly manage their workout (loss mitigation) programs. The FFIEC defines a workout program as:

> A former open-end credit card account for which credit availability is closed and the balance owed is placed on a fixed repayment schedule in accordance with the modified terms and conditions. Generally, these repayment terms require liquidation of the balance owed over a defined payment period. Such arrangements are typically used when a customer is either unwilling or unable to repay the open-end credit card account in accordance with its original terms, but shows the willingness and ability to repay the loan in accordance with its modified terms and conditions (Board of Governors of the Federal Reserve System, 2003).

One such program "*re-ages*" an account that has defaulted. According to the FFIEC guidelines, an issuer can re-age an account to current status given that the following criteria are met: (a) an account must be at least 9 months old; (b) the borrower makes three consecutive minimum payments over the next 3 months or within one billing cycle; (c) the issuer cannot re-age an account more than once in 12 months or more than twice in 5 years; (d) the cardholder must demonstrate willingness and ability to repay the debt to the creditor. Ambrose and Capone (1996) point out that liquidity constrained mortgage borrowers are more likely to avail themselves to a forebearance option.

## Literature Review

In order to determine whether a credit card debt should be fully charged-off, the lender should consider the probability of a permanent default. One main factor generally used to predict this probability is the borrower's relative credit risk profile (measured by FICO and internal behavioral scores), controlling for social factors (divorce rates, medical coverage, etc.), macroeconomic environment (unemployment, seasonality, etc.), as well as legal and state stipulations (garnishment, homestead and property exemptions levels).

Gross and Souleles (2002) conducted an empirical analysis of the demand for unsecured (credit card) debt and its impact on consumer default. They estimated a duration model using account-level data to assess the relative importance of various factors in predicting credit card defaults. In particular, they assessed the impact of: (a) FICO and Behavioral credit risk scores; (b) age (seasoning); (c) calendar time, and; (d) social and macro factors such as divorce rates and unemployment rates respectively on credit card default. They found that credit risk, seasoning, time, macro and social factors were statistically significant in determining credit card defaults.

Agarwal and Liu (2003) further studied the impact of unemployment over time as opposed to across states on credit card defaults. Using account level data, for over 700,000 accounts from 1995 to 2001, covering the recent recession, the authors found that credit card default rates varied with local unemployment conditions over time. Finally, Agarwal et al. (2003) empirically tested whether homestead, personal property, and garnishment exemptions across states played any part in the consumers' decision to become delinquent and eventually declare bankruptcy on their credit card debt. Agarwal et al. (2005) studied the effect of exemption laws on small business credit cards and found similar results. Empirical results indicated that homestead exemption levels were positively and statistically significant in determining an individual's decision to declare bankruptcy.

While the above studies looked at credit card default behaviors, none of them modeled the risk of a second default, conditional on being re-aged. This limits the usefulness of these studies to quantify the success of loss mitigation programs discussed earlier. In this paper, we estimate jointly the likelihood of a first and second credit card default following the methodology applied by Ambrose and Capone (2000), which estimates the hazard of first and second mortgage default conditional on reinstatement out of initial default.

## Data and Methodology

### Data

This study uses a proprietary data set provided by a large financial institution that issues credit cards nationally. The data set includes 241,452 individual accounts originated between January 1995 and December 1998 with performance information through December 2001. There are several aspects of this data set that are particularly conducive to studying the differences in the relative hazards of first and second defaults. Of the total number of accounts, 16,427 (6.8%) defaulted; 4,361 (26.5%) of the defaulted accounts were re-aged; and 971 (22.2%) of the re-aged accounts defaulted for a second time. These statistics are fairly representative of credit card performance during this period. Though the numbers of re-aged and second default accounts as percentage of the overall are 1.8% and .4%, they still represent 26.5% and 22.2% of re-aged and second default accounts conditional on first default and re-aging, respectively. Hence, there is a large gap between the first and second default percentages. The average age in months for an account to be classified as first default, re-aged, and subsequently second default are 22, 15, and 9 months, respectively. Here the age of a re-aged account implies the number of months an account is on books once re-aged but did not default for the second time.

The data set had all the variables that were collected at the time of account origination and maintained or updated throughout the period. If an account originated in January 1995 and the account was still in good standing, then we had performance data for the entire eight-year period. If an account originated in January 1995 but defaulted in February of 1996, re-aged in June of 1996 and subsequently defaulted in January of 1997, the panel truncated. Data include 13 months of performing data for (January 1995–1996), 4 months non-performing data (February 1996 to May 1996), 7 months performing data (June 1996 to December 1997), and 1 month of non-performing data (January of 1997).

Performance indicators of credit card accounts include: (a) delinquency indicators, (b) bankruptcy indicators, (c) default indicator, (d) re-age counter, (e) re-age date, and (f) other variables that characterize an account standing with the lender. As described earlier, a cardholder is allowed to re-age his/her account once in 12 months and twice in 5 years. Unfortunately, we cannot distinguish between the first and second *re-age*, so for our purposes we will consider them to be the same. The data set also includes a number of other bureau demographic variables, but we do not include them as part of this study because they are collinear with the bureau credit score. Factors that affect credit card defaults include (a) individual account quarterly bureau credit (FICO) score updates, (b) internal monthly behavioral score updates, (c) borrower's self-reported personal income at origination, (d) credit limits, (e) monthly payment histories, and (f) monthly interest charges. For a thorough understanding of the bureau data (see Avery et al. 2003). Together, performance indicators and the default determinants enable us to use the hazard function as described in Ambrose and Capone (2000).

Table 1 provides descriptive statistics. The interest rates for current, first and second default accounts averaged 14.9%. The credit limits for current, first and second default accounts averaged $3,000. The mean debt-to-income ratio at account origination was 40.7% for current accounts, 48.8% for first default accounts, and 46.1% for second default accounts. Credit card debts averaged $165 for current accounts, $767 for first default accounts, and $986 for second default accounts. Due to the proprietary nature of the data set we cannot provide additional descriptive statistics for the variables. The average external (FICO) score was 706 for current accounts, 631 for first default accounts, and 658 for second default accounts, while the average internal behavioral credit score supplied by the lender was 701 for current accounts, 642 for first default accounts, and 691 for second default accounts.

Explanatory variables include (a) county unemployment rates, (b) percentage of people without medical coverage, (c) divorce rates, and (d) other demographic and legal characteristics for each state. It is worth noting that four states (California, Colorado, Indiana,

**Table 1** Summary statistics

| | Current accounts | First default | Second default |
|---|---|---|---|
| Debt to income | 40.78 | 42.04 | 39.82 |
| APR | 14.9 | 14.9 | 14.9 |
| Debt | 165 | 767 | 986 |
| Account limit | 3,000 | 3,000 | 3,000 |
| External score | 706 | 631 | 658 |
| Internal score | 701 | 642 | 691 |

and Louisiana) do not report divorce rates; whereas two other states (Nevada and Texas) do not have a complete time series for the time period covered in our study (see www.cdc.gov/nchs/nvss.htm). As evident from the PSID survey of participants that filed bankruptcy between 1984 and 1995, it was reported that (a) 12.2% filed due to loss of job, (b) 14.3% filed due to divorce, (c) 41.3% filed due to credit mismanagement, (d) 16.4% filed due to health related cost not covered by insurance, and (e) 15.9% filed due to lawsuit related costs. These statistics indicate that shock effects are significant contributors of bankruptcy. For the purpose of this study, we followed the performance of accounts for 4 years after origination in January 1995. We conducted similar analyses with a shorter performance window of 2 and 3 years and the results were qualitatively the same. However, Gross and Souleles (2002) showed that the probability of delinquency rises all the way until 24–30 months. For example, an account that originated in January 1995 was tracked until December 1998. If the account filed for bankruptcy or was 90 days past due at any time within the 4 years a default flag was created for that account. However, if the account was re-aged and reverted to a current standing and with subsequent filing for bankruptcy or 90 days past due, a second default flag was created. Furthermore, accounts with a flag indicating lost, stolen, never active, closed due to fraud/death were excluded from the analyses.

## Methodology

We estimated a duration model for first and second default following Ambrose and Capone (2000). Shumway (2001) identified three reasons for using a duration model as opposed to a static model: (a) static models fail to control for time specific risk; (b) duration models incorporate time varying covariates; and (c) duration models produce more efficient out-of-sample bankruptcy estimates by utilizing more data. The term *survival* indicated that a loan does not default but *survives* a period in time. Duration measures the length of time that extends from the beginning until a specified event (e.g., default) occurs. The hazard function provides an estimate of the likelihood of default in any given period conditional upon exogenous explanatory variables known as covariates and *survival* (non-default) or prior default with re-age option up to that period. We used a proportional hazard model to analyze the underlying distribution of credit card duration and to assess the marginal effects of the explanatory variables on the duration.

The instantaneous probability that a particular credit cardholder (i) will default, where $D_{i,t}$ indicates whether an account $i$ defaults in month $t$, is as follows:

$$D_{i,t} = h_0(t)\exp(\beta' X_i(t)) \tag{1}$$

where $h_0(t)$ is the baseline hazard function at time $t$ (the hazard function for the mean individual in the sample; *Seasoning* [the age of the account] and *Time* [time dummies corresponding to calendar month] were used as proxies of the baseline hazard; $X_i(t)$ is a vector of time-varying covariates; $\beta$ is the vector of unknown regression parameters to be estimated; and $\exp(\beta' X_i(t))$ is the exponential distribution specification that allows us to interpret the coefficients on the vector of $X$ as the proportional effect of each of the exogenous variables on the conditional probability of completing the spell, e.g., credit card termination.

As implemented by Ambrose and Capone (2000), following Flinn and Heckman (1982) and Allison (1995), we estimated a model for the time to second default [see Ambrose and Capone (2000) for a detailed description of the underlying methodology]. To capture the impact of various explanatory factors on both the first and second default, we interacted the independent variables with a second default dummy as follows:

$$\begin{aligned}\beta' X_{i,t} = \sum_{j=1}^{2} (&\beta_{1,j}\ \text{State/County}_{i,j} + \beta_{2,j}\ \text{AccountBalance}_{i,t,j} + \beta_{3,j}\ \text{CreditLimit}_{i,t,k} \\ &+ \beta_{4,j}\ \text{APR}_{i,t,j} + \beta_{5,j}\ \text{BehaviorScore}_{i,t,j} + \beta_{6,j}\ \text{FICOScore}_{i,t,j} \\ &+ \beta_{7,j}\ \text{Divorce}_{i,t,j} + \beta_{8,j}\ \text{Unemployment}_{i,t,j})\end{aligned} \tag{2}$$

where $i$ represents the $i$th account, $t$ represents the $t$th month, and $j$ represents first or second default [$j = 1$ for first default, and $j = 2$ for second default]. State/County represents state or county dummies corresponding to the 50 states or over 3,000 counties. We estimated several specifications of the above general model to check for robustness of our results.

As discussed in the previous section, unsecured credit markets (i.e., lines of credit) are particularly vulnerable to endogeneity in the credit supply and demand variables for two main reasons: (a) the debtor can choose to increase (decrease) credit demand if they feel the option to default (prepay) is in-the-money and (b) the creditor can choose to increase/decrease credit supply if he/she feel that option to default/prepay is not in-the-money. Unlike the mortgage payment, which is fixed on a monthly basis, the credit line is an open buy-to-sell option for the cardholder. For example, the cardholder can choose to raise the utilization rate to as much as 100% if she is 90 days delinquent in her debt payments. At the same time, lenders will initiate several steps to effectively limit the delinquent cardholder's access to credit supply. This can be accomplished in several ways. For instance, the lender can reduce the credit limit to the current balance level and effectively force the cardholder to be credit constrained. The lender can also restrict the ability to access credit elsewhere by lowering the credit bureau score. Furthermore, they can also raise the interest rate and further constrain the ability to pay back the loan. In turn, the lender's actions would have an effect on borrower's credit demand from existing sources of credit (re-aged credit card) and the ability to access new sources of credit (apply for a new card). Hence, it is particularly important that we address credit supply and demand endogeneity for second default.[2]

In view of the above discussions, we controlled for credit risk factors such as FICO and behavior scores, interest rates, and credit limit 6 months prior to default. This will help distinguish credit supply endogeneity. However, the cardholder could act strategically and alter credit demand prior to default to take advantage of the bankruptcy exemption laws (see Agarwal et al. 2003). Hence, we also controlled for account balance at 6 months prior to default.

We expected FICO and behavior scores to be negatively related to default since higher scores imply the borrower has relatively lower credit risk. Credit limit should also be negatively related to the likelihood of a cardholder defaulting since lower risk consumers generally qualify for higher credit limits. A higher debt service burden makes a cardholder more vulnerable to adverse income shocks that may reduce his ability to repay his debt; hence, amount balance should be positively related to the likelihood of default. Similarly, higher APR should also increase the likelihood of default because higher interest rates

[2] We are particularly concerned about the endogeneity in the case of second default since it is relatively easy to control for endogeniety in first default. For instance, we could control for scores, lines, and other risk variables just before the account is 30 days delinquent as opposed to at the time of default. This issue is also discussed in Gross and Souleles (2002) and Agarwal and Liu (2003).

amplify the debt service burden and increase the probability of default. Finally, we expect that both divorce rates and unemployment rates can cause unexpected liquidity shocks and, thus, are expected to increase the likelihood of default. We discuss our empirical findings in the following section.

## Empirical Findings

We first estimated the baseline survival functions by state—the cumulative likelihood of a loan *surviving* (i.e., not being delinquent) over time.[3]

Figure 1 presents the baseline survival functions for first and second default based on the mean values for all the independent variables over the sample period. These estimated survival functions indicate that—under the homogeneous market conditions faced by the borrower in our sample—nearly five out of every 1,000 (or .5%) re-aged accounts defaulted a second time during the first 6 months of re-aging or account origination, as compared to only one out of 1,000 (or .1%) originated account defaulted for the first time. While the second default rate is higher in the first 2 years after reinstatement than the first default rate in the first 2 years after origination, the second default rate is higher than the first default rate after 2 years.

Table 2 presents the estimation results of the proportional hazard model. Given demand and supply endogeneity discussed earlier, we estimated a model specification controlling for the risk factors observed at 6 months prior to default, such as FICO $\text{Score}_{t-6}$, Behavior $\text{Score}_{t-6}$, and Line $\text{Amount}_{t-6}$.[4] The results show that FICO and behavioral scores, as well as line amount, have negative and statistically significant impact on the risk of a first default. On the other hand, while the statistically significant and negative impact of a FICO score and line amount on the risk of a second default meets our expectation, the significantly positive coefficient of the behavioral score is counterintuitive. We believe this is mainly due to the fact that the internal delinquency flag on the card is reset to current and a payment is posted on the account, resulting in an automatic and immediate rise in the behavioral score. In this case, the automatically inflated behavioral score of reinstated accounts does not capture the true relative credit risk of the borrower. Hence, risk management should be cautious when using internal behavioral scores to predict the second default risk of reinstated loans.

We estimated the marginal impact of both the behavioral and FICO scores 6 months prior to first and second default. The results suggest that for every 20 points drop in a FICO score, the likelihood of first default rises by 9% while the likelihood of second default rises by 16%. On the other hand, for every 20 points drop in the behavioral scores, the likelihood of first default rises by 19% while second default rises by 7%. These results clearly suggest that FICO scores are better predictors of second default, and behavior scores are better

[3] The baseline survival function can be thought of as the survival curve of an average consumer, someone for whom each predictor variable is equal to the average value of that variable for the entire set of consumes. In the partial likelihood framework, the survival function can be estimated from the semiparametric estimator $S(\tau, x_{it}) = (S_0(\tau))\exp(x_{it}\beta)$ where $S_0(\tau)$ represents the baseline survival function. For additional references, see the SAS procedure proc phreg.

[4] We also ran a number of other regressions to control for state variables at 9 and 3 months as opposed to 6 months. Other regressions also include, nonlinear terms for risk (internal and external scores and line account) and macro/social variables: like garnishment, homestead and property exemptions and interest rates, debt to income at account origination and others. However, the results are quantitatively the same and so we do not report those results.

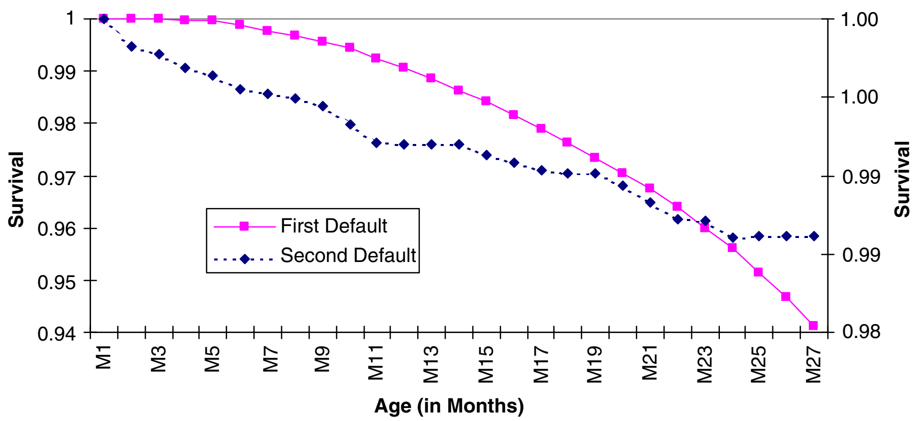


**Fig. 1** Survival function for first and second default

predictors of first default. These results are fairly intuitive. FICO scores, which capture the relative credit risk profile of a borrower overall, serve as a better predictor of both the first and second default. On the other hand, behavior scores that reflect internal re-payment behaviors, including the current payment status following reinstatement, of the borrower on this particular card do not accurately capture the true relative credit risk of the borrower, and thereby cannot predict the second default.

Other control variables are highly predictive of both first and second default. For instance, account balance, county unemployment rates, and state average income are all positive and significant. However, a flag for no medical coverage is only predictive for the second default, but not for the first default. Finally, state fixed-effects are jointly significant, similarly calendar time fixed-effects are also jointly significant, and account age (seasoning) polynomials are also highly significant. As discussed earlier, we include dummy variables for all 50 states or 3,000 counties to control for state specific fixed effects. Similarly, we included monthly dummy variables for calendar time from 1995 to 2001. Finally we also included dummy variables for account age. Account age does not necessarily coincide with month dummies.

Finally, our data sample of re-aged and subsequent second default accounts indicates that 78% of the re-aged accounts stay current on their credit card payments. Moreover, average FICO scores for the 78% of re-aged consumers rose by as much as 20 points after they had been re-aged, indicating that an improvement in their overall risk profile. These findings suggest that the re-aging program does provide a second chance for liquidity-constrained consumers who would have otherwise default on their debt.

## Conclusion

Using a unique data set of account level credit card defaults for a 7-year period (January 1995 to December 2001), we assessed the extent to which reinstated (i.e., *re-aged*) credit card accounts default again compared to those defaulting for the first time. We found that about 22% of reinstated credit cardholders do default again, while 78% stay current, after their first default status has been reinstated. Overall, reinstated credit cardholders have a higher risk of a second default than those cardholders defaulting for the first time in the first

**Table 2** Hazard model estimates of first and second credit card default[a]

| First default | Estimated coefficient | $p$-value |
|---|---|---|
| FICO score$_{t0}$ | | |
| Behavioral score$_{t0}$ | | |
| Line amount$_{t0}$ | | |
| FICO score$_{t-6}$ | −.001550 | .0013 |
| Behavioral score$_{t-6}$ | −.002080 | <.0001 |
| Line amount$_{t-6}$ | −.000498 | <.0001 |
| Account balance$_{t-6}$ | .000582 | <.0001 |
| State average income$_{t-6}$ | .000002 | <.0001 |
| No medical coverage$_{t-6}$ | .002070 | .9675 |
| Unemployment$_{t-6}$ | .004900 | .0277 |
| Second default | | |
| FICO score$_{t0}$ | | |
| Behavioral score$_{t0}$ | | |
| Line amount$_{t0}$ | | |
| FICO score$_{t-6}$ | −.000696 | <.0001 |
| Behavioral score$_{t-6}$ | .001360 | <.0001 |
| Line amount$_{t-6}$ | −.000278 | <.0001 |
| Account balance$_{t-6}$ | .000264 | <.0001 |
| State average income$_{t-6}$ | .000006 | <.0001 |
| No medical coverage$_{t-6}$ | .015440 | .0797 |
| Unemployment$_{t-6}$ | .002460 | .0357 |
| State fixed effects | Yes | |
| Account age fixed effects | Yes | |
| Year/month fixed effects | Yes | |
| Number of accounts | 241,452 | |
| Log likelihood | 2,384 | |
| Pseudo $R^2$ | .28 | |

[a] The table reports results of a hazard model of first and second default (defined as 90 days past due) using monthly account level data from January 1995 to December 2001. Explanatory variables include account-specific risk factors: external score, internal score, and line amount; subscript t0 represents the control variables at account origination, and t−6 represents the control variables 6 months prior to default. Other explanatory variables we control for are: calendar time, account seasoning, state fixed effects, and other shock effects like state divorce rates, state health care coverage, and county unemployment rates

24 months on book. After this 2-year period, however, baseline default patterns indicate a lower risk of a second default for reinstated accounts compared to those defaulting for the first time. Moreover, average FICO scores for the 78% of re-aged consumers rose by as much as 20 points after they had been re-aged, indicating that there is an improvement in their overall risk profile. These results provide support for the notion that offering forbearance plans overwhelmingly helps liquidity constrained consumers to cure out of default.[5]

[5] Another mechanism, besides re-aging, through which forbearance plans could potentially reduce credit losses, is credit counseling. Collins (2007) found that each additional hours of counseling reduced the marginal probability of default and foreclosure.

We also estimated a duration model to analyze the relative importance of external and internal credit scores in predicting first and second defaults. After controlling for (a) calendar time effects, (b) age (account seasoning), (c) state/county specific effects, and (d) macro/social shock effects (divorce, health costs, unemployment), we found that FICO scores (public information) are better predictors of a second default, while payment behavioral scores (private information) are better predictors of a first default. Given that a FICO score captures the relative credit risk profile of a borrower (as measured from credit bureau data) including the risk of other outstanding credits at other financial institutions after re-aging, it is reasonable that the FICO score is a better predictor of a second default. An internal payment behavioral score, on the other hand, may not fully capture the relative credit risk profile overall once an account is re-aged.

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