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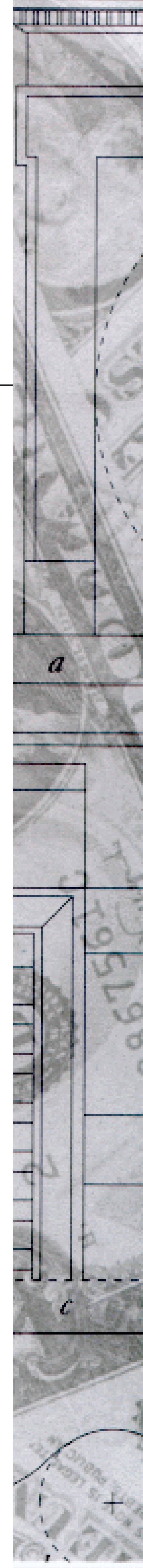

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An Empirical Analysis of Personal Bankruptcy and Delinquency

by
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An Empirical Analysis of Personal Bankruptcy and Delinquency [†]

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Abstract

This paper uses a unique new panel data set of credit card accounts to analyze credit card delinquency and more generally personal bankruptcy and the stability of credit risk models. We estimate duration models for default and assess the relative importance of different variables in predicting default. We investigate how the propensity to default has changed over time, disentangling the two leading explanations for the recent increase in default rates – a deterioration in the risk-composition of borrowers versus a reduction in the social stigma of default. Even after controlling for risk-composition and other economic fundamentals, the propensity to default significantly increased between 1995 and 1997. By contrast, increases in credit limits and other changes in risk-composition explain only a small part of the change in default rates. Standard default models appear to have missed an important time-varying default factor, consistent with the stigma effect.

JEL classification: E21; E51; G21; G33

Keywords: Personal bankruptcy; Forecasting default; Credit risk management; Consumer credit; Credit cards

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Abstract

This paper uses a unique new panel data set of credit card accounts to analyze credit card delinquency and more generally personal bankruptcy and the stability of credit risk models. We estimate duration models for default and assess the relative importance of different variables in predicting default. We investigate how the propensity to default has changed over time, disentangling the two leading explanations for the recent increase in default rates – a deterioration in the risk-composition of borrowers versus a reduction in the social stigma of default. Even after controlling for risk-composition and other economic fundamentals, the propensity to default significantly increased between 1995 and 1997. By contrast, increases in credit limits and other changes in risk-composition explain only a small part of the change in default rates. Standard default models appear to have missed an important time-varying default factor, consistent with the stigma effect.

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1. Introduction

Debt issued by consumers is an under-studied asset class. There has been particularly little study of recent trends in default on this debt. Between 1994 and 1997 the number of personal bankruptcy filings in the U.S. rose by about 75%. The 1.35 million filings in 1997 represented well over 1% of U.S. households. Delinquency rates on credit cards rose almost as sharply. (Federal Reserve Board of Cleveland, 1998) The resulting losses to lenders amounted to a sizeable fraction of the interest payments they collect, potentially raising the average cost of credit. These trends in default, both in bankruptcy and delinquency, are especially surprising in light of the strong economy over the period. They provide an unusually rich source of variation to test the stability of models that forecast personal default and of credit risk models more generally.

There are two leading explanations given for these trends. First, the risk-composition of borrowers might have worsened. Under the "risk effect," less credit-worthy borrowers obtained additional credit in recent years, and it is these borrowers who accounted for most of the rise in default. In particular, many analysts cite growth in the number of credit card offers and in the sizes of credit card lines as the most important factors behind the rise in default. (See e.g. the New York Times, 1998.)

The second explanation is that there might have been a decline in the social stigma associated with default or an increase in knowledge about default. Stigma can be thought of as part of the cost of default, both non-pecuniary (e.g., disgrace) and pecuniary (e.g., the consequences of a bad reputation). Many analysts argue that these costs have recently declined, especially as default has become more commonplace. Default, in particular filing for bankruptcy, also entails information and legal costs, which might likewise have declined. Here analysts often cite growth in the number of bankruptcy lawyers and their advertising (as prohibitions on advertising were loosened), as well as in other sources of advice like “how-to-file” books. Further, the flow of informal advice from family and friends might have accelerated as more people have been through bankruptcy.[1] Even a small decline in these various costs could substantially increase default rates, considering White (1997)’s estimate that between 15% and 31% of U.S. households could benefit, just in terms of their current net worth, by filing for bankruptcy. Generalizing these arguments, by the “stigma effect” we mean quite broadly that people have become more willing to default over time, even controlling for their risk characteristics and other standard economic fundamentals.

It can be important to determine the relative significance of these two alternative explanations. Unlike the risk effect the stigma effect represents a change in the relationship between default and the economic fundamentals that lenders typically use to predict default, such as debt levels. Their default forecasting models would then be missing some systematic and time-varying factor, and hence be unstable. This could potentially result in the misallocation or mispricing of credit. Unlike a deliberate expansion in the supply of credit, an unexpected decline in stigma would lead to greater credit losses than expected. While lenders can respond to increased losses from either effect by improving the risk-composition of their portfolios, a broad-based decline in stigma might require more substantial changes in credit policy. As regards public policy, some policy makers subscribing to the risk effect have advocated restricting credit supply in order to improve the risk-composition of the borrowing population. Others, subscribing to the

[1] Weller (1998) provides a typical exposition of these arguments: "Just as attorney advertising has enhanced the public's awareness of bankruptcy as a financial escape hatch and bankruptcy reform has made filing less time consuming than renewing a driver's license, the stigma of bankruptcy has become a shadow of its former self. The names of good bankruptcy attorneys and stories about the ease of getting out of debt are passed around the water cooler like football scores on a Monday morning in October."

stigma effect, have advocated making the terms of bankruptcy less attractive in order to increase the perceived costs of default.

Unfortunately it has been difficult to disentangle the risk and stigma effects empirically. First, it is not obvious how to operationalize the stigma effect. Most of the proxies for stigma that have been suggested run into problems of endogeneity and reverse causality.[2] A second difficulty is that controlling for risk-composition requires measures of credit supply and credit risk for a large sample of borrowers, including a large number of borrowers who have defaulted. As in the literature on corporate default, traditional household data sets do not provide enough such information.

This paper uses a new data set containing a panel of several hundred thousand individual credit card accounts from several different credit card issuers. The data set is of very high quality. It includes essentially everything that the issuers know about their accounts, including information from individuals' credit applications, monthly statements, and credit bureau reports. In particular, the data set records cardholder default (both delinquency and bankruptcy) and contains a rich set of measures of credit risk including debt levels, purchase and payment histories, credit lines, and credit risk scores, the issuers' own internal summary statistics for risk.

We use this data to analyze credit card delinquency and more broadly personal bankruptcy and the stability of credit risk models. Aggregate credit card debt currently amounts to over $500 billion, much of which is securitized, so credit card default is of interest in itself. Further, because about 75% of U.S. households hold credit cards, and our data set includes credit bureau data which pertains to all sources of consumer credit, not just credit cards, we are able to study

[2] For example, consider using the number of advertisements by bankruptcy lawyers as an inverse proxy for stigma. The problem is that an increase in ads might not be the *cause* of the rise in bankruptcies, but rather their *effect*. The increased

personal bankruptcy and default in general. Total consumer debt amounts to about $6T, $1.3T even excluding mortgages (Federal Reserve System, 1999). Relative to the assets side of household balance sheets, there has been surprisingly little analysis to date of the liabilities side, largely for lack of data. Finally, empirical models of personal and corporate default are in many ways analogous. On the corporate side, Saunders (1999) emphasizes the same two difficulties discussed above: the paucity of data, especially the limited number of observations of default; and the potential instability of default models over time, especially over the business cycle. In contrast, our data allows us to study a large number of defaulters over a concentrated sample period, 1995-1997, of benign macro-economic conditions. Finding model instability in such a sample would be a relatively strong result.

Specifically, we estimate duration models for default, for both bankruptcy and credit card delinquency, and assess the relative importance of different variables in predicting default. The estimated models allow us, for example, to evaluate the quality of commercial credit scores as predictors of bankruptcy or delinquency. Are the scores optimal predictors of default, incorporating all information available to the issuers? In addition, are younger accounts and accounts with larger credit lines more likely to default? We also investigate how the propensity to default has changed over time, disentangling the risk and stigma effects. Since the data include the information that the card issuers themselves use to measure risk, we are able to control for all changes in the risk-composition of accounts that were observable by the issuers. This allows us to assess the stability of default models from the point of view of a lender trying to forecast default.

A key finding is that the relation between default and economic fundamentals appears to have substantially changed over the sample period. Even after controlling for risk-composition

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bankruptcies could be due to the risk effect, with lawyers responding to the increased demand for their services by and other standard economic variables, the propensity to default significantly increased between 1995 and 1997. A credit card holder in 1997 was almost 1 percentage point more likely to declare bankruptcy and 4 percentage points more likely to go delinquent than a cardholder with identical risk characteristics in 1995. These magnitudes are approximately as large as if the entire population of cardholders had become one standard deviation riskier, as measured by credit risk scores. By contrast, increases in credit limits and other changes in risk-composition explain only small part of the change in default rates over time. Standard default models appear to have missed an important, systematic and time-varying default factor, consistent with the stigma effect.

Section 2 of the paper describes the data used in the analysis and Section 3 discusses related studies. Section 4 develops the econometric methodology and Section 5 reports the results. Conclusions appear in Section 6.

2. Data description

The authors have assembled a panel data set of several hundred thousand credit card accounts from several different credit card issuers. The accounts are representative of all open accounts in 1995. Because the issuers include some of the largest credit card companies in the U.S., the data should be generally representative of credit card accounts in the U.S. in 1995.[3] The individual accounts are then followed monthly for 24 to 32 months. Different credit card issuers track somewhat different sets of variables at different frequencies depending on whether the variables come from cardholders' monthly statements, credit bureau reports, or credit

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additional advertising.

applications. To protect the identity of the accounts and the issuers, the data from different issuers were pooled together, with great care taken to define variables consistently across issuers. The results that are reported will only use variables common to all the issuers. However, the results were checked for robustness separately for each issuer, using that issuer's complete set of variables. Table 1 provides summary statistics for the main set of variables used below.

This data has a number of unique advantages compared to traditional household data sets like the Survey of Consumer Finances (SCF) or the Panel Study of Income Dynamics (PSID). First, the large cross-section of accounts contains many thousands of observations of even low probability events like delinquency and bankruptcy. Second, the long time series makes it possible to estimate explicitly dynamic models of default. Third, in contrast to data based on surveys of households, measurement error is much less of a problem. Fourth, the data contains essentially all the variables used by issuers in evaluating accounts. Using account data does, however, entail a number of limitations. The main unit of analysis in the data is a credit card account, not an individual. We partially circumvent this limitation by using data from the credit bureaus, which cover all sources of credit used by the cardholder, and by examining credit card delinquency in addition to bankruptcy. Also, there is little information about some potentially important variables like household assets or employment status. However the study by Fay, Hurst, and White (1998) discussed below finds that the effects of such variables on bankruptcy are relatively small in magnitude.

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[3] As a check, the data were benchmarked against the more limited and self-reported credit card information in the 1995 Survey of Consumer Finances. The averages of most variables were in rough agreement, however preliminary analysis suggests that the SCF households underreport the amount of debt they actually rollover.

3. Related studies

Most empirical studies of default have focused on bankruptcy, concentrating on the effect of changes in the Bankruptcy Code in 1978 or on the effects of different exemption levels on filing rates across U.S. states. (For a review see Hynes, 1998.) These studies have generally used aggregated data, and hence do not address the role of risk-composition.

In their historical discussion of bankruptcy, Moss and Johnson (1998) note that the stigma effect has been proposed in the past to explain previous accelerations in bankruptcy rates, as in the 1920s and 1960s. In the absence of evidence, they warn against simply assuming the stigma effect is playing an important role today. Instead, they argue that increases over time in the amount of debt held by lower income households can potentially explain the recent rise in bankruptcy. This argument is a version of the risk-composition effect. Unfortunately the SCF, which Moss and Johnson use to identify the change in the distribution of debt, does not record whether people have filed for bankruptcy so they are unable to test their argument empirically. Since there have been changes in the income distribution of credit in the past, it does not follow that recent changes in the distribution explain current bankruptcy trends. The relative importance of risk-composition versus stigma is a quantitative question that can only be answered with suitable data.

Domowitz and Sartain (1999) try to circumvent the limitations of the SCF by combining it with a separate data set of bankruptcy petitions. They use this additional data essentially to estimate whether the households in the 1983 SCF have filed for bankruptcy. However, it can be difficult to estimate low-probability events like bankruptcy in a small, cross-sectional sample like the SCF.[4] The 1996 PSID contained a set of retrospective questions about bankruptcy. Fay, Hurst, and White (1998) use this data to try to identify the effects of stigma. Because the PSID also recorded data on household balance sheets in a number of years (1984, 1989, and 1994), the authors were able to estimate for each household in their sample the economic benefit of filing for Chapter 7, taken to be the value of debt that would be discharged minus assets (net of exemption levels) that would be relinquished. As an inverse proxy for stigma, the authors use the lagged bankruptcy rate in the state in which the household resides. They find that the probability of filing increases with both the economic benefit of filing and the inverse proxy for stigma. However, the magnitude of the increase is small in both cases. This paper differs from the Fay, Hurst, and White study in a number of ways. First, their PSID sample contains only about 250 observations of bankruptcy over the course of a 12 year period ending in 1995. Non-linear inference on such a small sample of households can be difficult.[5] Second, the PSID does not contain explicit measures of household credit risk like risk scores, nor measures of credit supply like credit lines.

The related literature on corporate default is much larger, though as already noted it too has been constrained by data limitations. Also, as Shumway (1998) emphasizes, much of the literature has used essentially static, cross-sectional specifications for default. By contrast the duration analysis used here will explicitly accommodate changes over time in the riskiness of a given borrower.

[4] To illustrate, the SCF sub-sample used in their analysis contains about 1,900 households. Even at today's bankruptcy rate of approximately 1%, which is much larger than the 1983 rate, the sub-sample would include only about 19 households that actually filed for bankruptcy.

[5] Fay, Hurst, and White estimate that their PSID households underreported the incidence of bankruptcy by about 50%, relative to aggregate statistics.

4. Econometric methodology

From the data set described in Section 2, we drew a representative sample of all credit card accounts open as of June 1995. This sample includes all accounts in good standing as of that month. Accounts that had been closed or frozen on or before June 1995 because they were bankrupt or three or more cycles delinquent are excluded.[6] These accounts were followed for the next 24 months, or until they first defaulted. This period from 1995:Q3 through 1997:Q4 covers the time of the sharp rise in default at the national level. Two indicator variables were created that identify the first month in the sample, if any, in which an account defaulted. The delinquency indicator, DEL, identifies the first time that a card failed to meet its minimum payment for three successive months, the standard industry definition of serious delinquency. The bankruptcy indicator, BK, identifies the month in which the card issuer was notified or learned from the credit bureaus that the cardholder filed for bankruptcy. Accounts that are both delinquent and bankrupt are counted as bankrupt. This yields about four thousand accounts going bankrupt, and fourteen thousand accounts going delinquent. A random sample of about ten thousand accounts that never default within the sample period is included as a control group. The delinquent and the bankrupt accounts are each separately compared to the non-default control group. The resulting samples overweight defaulting accounts, in predetermined proportions, in order to increase precision. All the results below are weighted to make them representative.

We shall estimate dynamic probit models for default, which on our samples are equivalent to discrete duration models. (See Shumway, 1998, for a helpful discussion of this equivalence.)

[6] To simplify the analysis of the age of a credit card account below, the main analysis does not include accounts opened before 1990. Given the recent growth in the number of accounts, this restriction retains most accounts. The conclusions below are unaffected whether or not these older cards are included.

For either the delinquency or bankruptcy sample, let $D_{i,t}$ indicate whether account i defaulted in month t. For instance an account which goes three cycles delinquent in month 10 would have D_{it}=0 for the first 9 months, $D_{i,10}$=1, and then drop out of the sample. Let $D^*_{i,t}$ be the corresponding latent index value. The main specification that will be estimated is given by equation (1):

$$D^*_{i,t} = \boldsymbol{b_0}'\boldsymbol{time_t} + \boldsymbol{b_1}'\boldsymbol{age_{i,t}} + \boldsymbol{b_2}'\boldsymbol{risk_{i,t}} + \boldsymbol{b_3}'\boldsymbol{econ_{i,t}} + h_{i,t}\,. \qquad (1)$$

$age_{i,t}$ represents the number of months that account i has been open by time t. This variable allows for "seasoning" of credit card accounts, e.g. accounts might become less likely to default as they age. Under the duration model interpretation of Eq. (1), it is $age_{i,t}$ that captures the duration dependence in default. The vector $\boldsymbol{age_{i,t}}$ represents a fifth-order polynomial in account age, to allow the associated hazard function to vary non-parametrically. $\boldsymbol{risk_{i,t}}$ and $\boldsymbol{econ_{i,t}}$ represent account-specific measures of risk and local economic conditions, respectively, and will be further described below. The time dummies, corresponding to calendar quarters, allow for shifts over time in the average propensity to default, for accounts of any age and risk characteristics and controlling for economic conditions. They capture other time-varying default factors.

It will be helpful to begin with a simpler specification. A probit model of delinquency was first estimated with only the time dummies and the fifth-order polynomial in account age as the independent variables, omitting $\boldsymbol{risk_{i,t}}$ and $\boldsymbol{econ_{i,t}}$. Fig. 1 displays the resulting predicted values. Each curve shows the effect of account age on delinquency, the non-parametric hazard function, for a different quarter. The age variables are statistically significant and large in magnitude. The inverted-U shape implies that the probability of delinquency rises from the time an account is booked until about its two-year birthday, and then declines. The time dummies are also significant, implying that the hazard functions shifted over time, and so the simple specification is unstable.

These shifts could reflect changes in the risk-composition of accounts or in other economic fundamentals over time. Eq. (1) controls for such changes. The available risk measures $\boldsymbol{risk}_{i,t}$ are quite comprehensive. They include direct, monthly observations of the performance of each account, such as debt levels, purchase and payment histories, and credit lines, as well as the credit risk scores, the issuers' own overall summary of the riskiness of each account. We will assess the relative importance of these variables in predicting default. Note that if the credit scores are sufficient statistics for default, no other variables available to the issuers should be significant predictors. $\boldsymbol{econ}_{i,t}$ controls for local economic conditions like the state unemployment rate (*unemployment*), the fraction of people in the state without health insurance (*no_insurance*), and the median real new house price in the region (*house_prices*). While *unemployment* is available monthly, *house_prices* is measured quarterly and *no_insurance* only annually. Monthly values for the latter two variables were linearly interpolated.

The age polynomial and the risk variables together control for the risk-composition of credit card accounts and therefore for the risk effect. If lending standards were loosened over time, recently booked accounts will have worse risk characteristics, and under the risk effect this would explain the rise in default. The time dummies identify changes over time in the average propensity to default that are not due to risk-composition or other economic fundamentals, and so capture omitted factors like stigma. It is of course possible that the time effects we identify with stigma are picking up some other measure of risk or other economic fundamental that we have not controlled for. However, Eq. (1) already contains a much richer set of controls than is available in the data used in previous studies. The controls used here include the variables tracked by the credit card issuers themselves, who have strong incentives to measure risk accurately. Further, in light of the strength of the economy in recent years, most other unmeasured economic fundamentals improved over the sample period and therefore would be unlikely to increase default rates.

There are multiple possible timing conventions that could be used for the risk controls $\boldsymbol{risk}_{i,t}$ in Eq. (1). To identify changes in booking standards over time, they might naturally be taken from the original time of application. However, application data would not control for changes in risk-composition or economic conditions between the time of application and the start of the sample. For example, the 1990-91 recession might have had lingering effects on people's ability to pay their debts. Taking the risk controls from the time of application would attribute all of this variation to stigma. Also, some issuers did not store some of their application variables, especially for the older accounts.

Instead, for the main results the risk controls are all taken from June 1995, the month before the start of the sample period (that is, month $t=0$). While $\boldsymbol{age}_{i,t}$ controls for the variable component of account risk, namely the baseline hazard function, $\boldsymbol{risk}_{i,0}$ controls for the fixed component. It allows the hazard function to vary across accounts that start the sample period with different risk characteristics. To test for the risk effect, we will essentially check whether the sample trends in default can be explained by riskier accounts progressing through the riskier parts of their life cycle (e.g., around their two-year birthday). For instance, suppose the youngest accounts in the sample, those opened in early 1995, have bad risk characteristics $\boldsymbol{risk}_{i,0}$. Then the default rate might have increased in 1997 because the risky (and relatively large) 1995 "cohort" of accounts hit its two-year birthday in 1997. By contrast, to test for the stigma effect, we will check whether all accounts – even accounts with the same risk characteristics, age, and other economic fundamentals – have become more likely to default over time. Using $\boldsymbol{risk}_{i,0}$ is also appropriate from the point of view of a lender (or investor) who at time 0 is trying to forecast future default rates in a portfolio. Forecasting over a two-year horizon is consistent with industry practice; in particular the credit risk scores are usually calibrated on two-year samples.

Another possible timing convention would be to use updated, contemporary risk controls, $\boldsymbol{risk}_{i,t}$. But updating the risk controls would confound the risk and stigma effects because many of the risk variables are under the direct control of the consumer. For instance, people could have chosen to take on more debt over the course of the sample period because the stigma of default has fallen. Using $\boldsymbol{risk}_{i,t}$ would attribute all of this variation to the risk effect, thereby understating the stigma effect. One of the variables in $\boldsymbol{risk}_{i,t}$, however, is directly under the control of the issuers, namely the credit line. Therefore we sometimes replace the initial line, $line_{i,0}$, with the updated line, $line_{i,t}$, keeping the other, demand-determined risk controls at their initial values. This allows us to test whether increases in credit lines – the intensive margin of credit supply – have contributed to the default rate during the sample period.[7]

Aggregate credit supply during the sample period also changed along the extensive margin, through the introduction of new accounts. Since our sample is representative of accounts already open in mid 1995, it does not include accounts that opened subsequently. Hence the results do not include the contribution of these youngest accounts to national default rates between mid 1995 and mid 1997. However, this is not a problem for our analysis. The stigma effect should be independent of the characteristics of individual accounts, and the results will fully

[7] Of course, the issuers endogenously choose the credit lines on the basis of cardholders' past behavior, so using even the updated line could understate the stigma effect. In a companion paper, Gross and Souleles (1999), we explicitly examine the endogeneity in the supply of credit, and cardholder response to changes in supply. Note that under any of the timing conventions, the risk controls incorporate some supply effects (e.g., issuers' decisions to offer credit to

capture the contribution of the risk-composition of the accounts that are in the sample, to the default rates in the sample.

Both dynamic probit and logit models of Eq. (1) were estimated. Because the results were both qualitatively and quantitatively similar, we report only the probit results. The standard errors allow for heteroscedasticity across accounts as well as dependence within accounts. Dummy variables for the issuers are included but not reported. Various extensions of Eq. (1) will also be considered.

In order to evaluate how changes in stigma and risk-composition affect the probability of default, we want to compute the marginal value of varying each effect independently, at different times in the sample period. This requires a generalization of the marginal effects that are usually computed. Let Φ be the normal CDF (for the probit specification), and for any variable x let $\overline{x_{i,t}} = \frac{1}{N}\sum_{i=1}^{N} x_{i,t}$ be the cross-sectional mean of x in quarter t. We can naturally define the marginal effect of changing stigma to be the effect on default rates of varying only the time dummies, holding all other variables in Eq. (1) equal to their cross-sectional means. As a baseline, marginal values will be calculated relative to the first quarter (1995:Q3). Thus, the marginal effect of the change in stigma between quarter 1 and quarter t is calculated as

$$\begin{aligned} stigma_t = {} & \Phi\left(\boldsymbol{b_0}'\,\boldsymbol{time_t} + \boldsymbol{b_1}'\,\overline{\boldsymbol{age_{i,1}}} + \boldsymbol{b_2}'\,\overline{\boldsymbol{risk_{i,0}}} + \boldsymbol{b_3}'\,\overline{\boldsymbol{econ_{i,1}}}\right) - \\ & \Phi\left(\boldsymbol{b_0}'\,\boldsymbol{time_1} + \boldsymbol{b_1}'\,\overline{\boldsymbol{age_{i,1}}} + \boldsymbol{b_2}'\,\overline{\boldsymbol{risk_{i,0}}} + \boldsymbol{b_3}'\,\overline{\boldsymbol{econ_{i,1}}}\right) \end{aligned} \tag{2}$$

different risk groups) and some demand effects (e.g., people's decisions to open accounts and how much to borrow). Thus, the estimated risk effect represents an upper bound on the effects of issuer supply decisions.

Symmetrically, we define the marginal effect of changing risk-composition over time to be the effect of varying all variables other than the time dummies, again evaluating at cross-sectional means:

$$
\begin{aligned}
riskcomp_t = {} & \Phi\left(\boldsymbol{b_0}' \boldsymbol{time_1} + \boldsymbol{b_1}' \overline{\boldsymbol{age_{i,t}}} + \boldsymbol{b_2}' \overline{\boldsymbol{risk_{i,0}}} + \boldsymbol{b_3}' \overline{\boldsymbol{econ_{i,t}}} \right) - \\
& \Phi\left(\boldsymbol{b_0}' \boldsymbol{time_1} + \boldsymbol{b_1}' \overline{\boldsymbol{age_{i,1}}} + \boldsymbol{b_2}' \overline{\boldsymbol{risk_{i,0}}} + \boldsymbol{b_3}' \overline{\boldsymbol{econ_{i,1}}} \right)
\end{aligned}
\tag{3}
$$

Standard errors for $stigma_t$ and $riskcomp_t$ are calculated using the delta method.

It is important to understand exactly what $riskcomp_t$ measures. First, to emphasize the difference between changes in stigma and changes in standard economic fundamentals, we include in *riskcomp* the effects of changes in economic conditions, by varying ***econ***. Second, since $\boldsymbol{risk}_{i,0}$ identifies the fixed component of each account's risk, it does not contribute to variation in risk-composition over the sample period. As a result in the baseline specification the changes in $riskcomp_t$ over time are all due to changes in the variable, hazard-rate component of risk-composition, $\boldsymbol{age_{i,t}}$, and in $\boldsymbol{econ_{i,t}}$. Once we have used $\boldsymbol{risk}_{i,0}$ to control for the fixed component of account risk, our identification scheme allows us to treat the marginal effects of risk and stigma symmetrically, by using $\boldsymbol{age_{i,t}}$ to control for changes in risk over time, and $\boldsymbol{time_t}$ to measure changes in stigma over time. For a given risk group, identified by the account-specific measures of risk in $\boldsymbol{risk}_{i,0}$, both time and age are allowed to have a non-parametric effect on the probability of default over time.

5. Results

The first column of Table 2 shows the baseline results from the probit model for bankruptcy. The estimated coefficients for the quarter dummies and age polynomial are followed by the coefficients for the risk controls and local economic conditions. Starting at the bottom of the column, the unemployment rate *unemployment* and house prices *house_prices* are significant with the expected signs: greater unemployment and weaker house prices are associated with more bankruptcies. The risk controls are jointly very significant. Because the credit scores are important summary statistics for risk, both their levels and squares are included. Two different scores are used. The internal risk score is based on the past behavior of the individual account, the external risk score from the credit bureaus is based on the behavior of the account holder across all sources of credit. For each score the linear and quadratic terms are together quite significant, with $\chi^2_{(2)}$ statistics of around 100. Their total effect has the expected sign: accounts with higher scores are much less likely to go bankrupt. The remaining risk controls include card balances, payments, and purchases all normalized by the credit line, and the line itself. The normalized balance, defined as the utilization rate, is specified as a series of dummy variables: *utilization1* to *utilization7* represent a utilization rate of 0, in (0,0.4], (0.4,0.7], (0.7,0.8], (0.8,0.9], and (0.9,1.0], and over 1.0, respectively. Not surprisingly, accounts with higher utilization rates are much more likely to go bankrupt. Accounts making smaller payments or larger purchases also go bankrupt more often, although the latter effect is not significant. Since variables other than the credit scores are statistically significant, the scores appear not to be optimal predictors of default. The coefficient on the line is insignificant, but will be discussed further below, along with additional risk controls. The age variables remain jointly significant although the associated age hazard function is less sharply peaked than in Fig. 1.

The coefficients for the time dummies are highly significant and increase almost monotonically. Thus, even after controlling for account age, balance, purchase and payment history, credit line, risk scores, and economic conditions, a given account was more likely to go bankrupt in 1996 and 1997 than in 1995. Some other systematic default factor must have deteriorated, consistent with the stigma effect.

To quantify the relative importance of the risk and stigma effects over time, we computed their marginal values, $riskcomp_t$ and $stigma_t$, for each quarter. The results appear in Column (1) of Table 3, and are graphed in Fig. 2. $riskcomp_t$ is initially flat and then declines. As expected the aging of the portfolio and improvements in economic conditions imply a decrease in the bankruptcy rate over time. The time dummies essentially capture the difference between this implied bankruptcy rate and the actual rate. The rising trend in $stigma_t$ suggests that the actual rate is increasingly larger than the implied rate. The magnitudes are much larger than for $riskcomp_t$ and are statistically and economically significant. The probability of bankruptcy in quarter eight is about 0.07 percentage points per month larger than at the start of the sample. At an annual rate this translates into almost a 1 percentage point increase in the bankruptcy rate, a substantial effect.

Another way to illustrate the magnitude of the stigma effect is to contrast it with the effect of increasing the risk score of every account in the data by one standard deviation. This represents a very large increase in the overall riskiness of the credit card portfolio. A one standard deviation increase in the internal risk score raises the average probability of bankruptcy by about 0.07 percentage points per month, approximately the peak value of $stigma_t$ in quarter eight. Thus, the estimated stigma effect increased the bankruptcy rate by about as much as had the entire portfolio become one standard deviation riskier – again a substantial effect. We similarly computed the effects of varying other risk controls. The values for stigma are always large in comparison.

The remaining columns of Table 2 present various extensions of this analysis for bankruptcy. The associated marginal effects appear in the corresponding columns in Table 3. Column (2) shows the effects of interacting the age polynomial with all of the risk controls $\boldsymbol{risk}_{i,0}$. This interaction allows the baseline hazard functions to have very different shapes across different risk groups. Table 2 shows the resulting coefficients on the primary, non-interacted variables. The interaction terms are significant for payments, purchases, and the two risk scores. In Table 3 the associated marginal values $stigma_t$ in Column (2) have decreased by about one-third in magnitude relative to baseline Column (1), but they remain significant and continue to rise over time. The marginal values $riskcomp_t$ now rise until quarter 4 but then decline.

Column (3) in Tables 2 and 3 shows the results using the updated credit limit (once lagged), $line_{i,t-1}$, to investigate the effects of changes in credit supply within the sample period. The other, demand-determined risk controls are maintained at their initial values. The coefficient on the credit line is significant at the 10% level but negative, implying that larger lines are associated with less default. This reflects the fact that issuers offered greater amounts of credit to the cardholders that they believed to be less risky. The coefficients on the time dummies and their marginal values $stigma_t$ do not change very much. These findings suggest that larger credit lines are not responsible for the recent rise in default.

Column (4) adds dummy variables for the state in which the cardholder resides. These variables control for fixed geographical effects on the propensity to default. For instance, additional credit might have recently been obtained by riskier households living in poorer states.

Similarly, regulations, judicial attitudes, and average household demographics differ across states. However, while the state dummies are jointly quite significant (not shown), they do not much change the pattern of results for $stigma_t$. A conditional logit model was also estimated to remove fixed effects by zip code, but did not change these conclusions.

As discussed above, it is difficult to operationalize more directly the various notions of stigma that have been proposed. Some of these emphasize the idea that social opprobrium and information about bankruptcy might change with the number of people in one's community, appropriately defined, that have already filed for bankruptcy. To operationalize this geographic view of stigma we use the aggregate bankruptcy rate in the state in which the cardholder resides, the smallest geographic unit for which data is available. We add to Eq. (1) the average of this rate over the previous two calendar quarters, denoted by $staterate_{t-1}$. As reported in Column (5), $staterate_{t-1}$ is statistically significant and its total effect is positive, as expected. The probability someone files for bankruptcy increases with the number of people in her state who filed in the recent past. Further, the marginal values $stigma_t$ have decreased to about 60% of their baseline values in Column (1). These results support the geographic view of stigma. The omitted default factor varies systematically across states. Of course, the relevant community within which stigma operates might not be one's state, so these results can be considered a lower bound for the effect of stigma.

The same analysis was undertaken using delinquency as the indicator of default. Tables 4 and 5 present the results for the different specifications and their corresponding marginal values. In the baseline specification, in Column (1), the pattern of coefficients on the risk controls is similar to that above for bankruptcy. Now *no_insurance* is significant, with lack of health insurance associated with more delinquency. Once again people with larger balances and lower risk scores are much more likely to default. (The linear and quadratic terms for the external score are jointly significant.) Even with these controls for risk, the coefficients on the time dummies are again highly significant. Fig. 3 graphs the corresponding marginal values. $stigma_t$ rises for six quarters, but unlike for bankruptcy it then plateaus. (The magnitudes are larger than in Fig. 2 for bankruptcy, but this is because delinquency is much more common than bankruptcy.) The peak value in quarter six of about 0.3 translates into almost a 4 percentage point increase in the annual delinquency rate. For comparison, increasing the internal risk scores by one standard deviation raises the average predicted probability of delinquency by about 0.5 percentage points, more than the peak value of $stigma_t$. In this sense too the stigma effect is weaker for delinquency than for bankruptcy.

The remaining columns in Tables 4 and 5 presents various extensions. Column (2) shows the results on interacting age with $\boldsymbol{risk}_{i,0}$. This time the interaction terms for payments and the scores are significant. Again the time dummies remain significant and retain their original pattern, although their marginal values $stigma_t$ have been reduced by about 20% in magnitude. In Column (3) the updated credit line $line_{i,t-1}$ is again negative and highly significant. Finally, adding state dummies does not change these conclusions, as reported in Column (4).

For both bankruptcy and delinquency, some additional risk controls were added to Eq. (1), in subsamples where they are available. These variables include the income and age (date of birth) of the cardholder, and credit bureau variables like the total number of bankcards held by the cardholder and total debt from all sources normalized by income. While such variables are generally significant in predicting default, the coefficients on the time dummies always remain significant and increasing (unreported). It appears that there has not been enough change in risk-composition to explain the variation in default rates over the sample period. This is consistent with the stigma effect.

6. Conclusion

This paper has used a unique new panel data set of credit card accounts to analyze credit card delinquency and more generally personal bankruptcy and the stability of credit risk models. We estimated duration models for consumer default and assessed the relative importance of different variables in predicting default. We also investigated how the propensity to default has changed over time, disentangling the two leading explanations for the recent increase in default – changes in risk-composition and reductions in stigma. Our data contains a much richer set of measures of risk-composition than previously available, including debt levels, purchase and payment histories, credit lines, and credit risk scores. Since these measures include the information that credit card issuers themselves use to measure risk, we were able to control for all changes in risk-composition that were observable by or deliberately induced by the issuers, including increases in credit lines. The risk controls are highly significant in predicting default. Accounts with lower credit scores were much more likely to default. Even controlling for the scores, accounts with larger balances and purchases, or smaller payments, were also more likely to default. Unemployment, weak house prices, and lack of health insurance were also associated with more default. Larger credit lines however were not associated with default, suggesting that issuers extended the larger lines to less risky accounts. Nonetheless, despite their significance these variables explain only a small part of the change in bankruptcy and delinquency rates over the sample period. In sum, neither the risk-composition of accounts nor economic conditions changed enough to explain default rates.

Instead, the relation between default and economic fundamentals appears to have substantially changed over the period. Even after controlling for risk-composition and other economic fundamentals, the propensity to default significantly increased between mid 1995 and mid 1997. A credit card holder in 1997 was almost 1 percentage point more likely to declare bankruptcy and 4 percentage points more likely to go delinquent than a cardholder with identical risk characteristics in 1995. These magnitudes are approximately as large as if the entire population of cardholders had become one standard deviation riskier, as measured by risk scores. Standard default models appear to have missed an important, systematic and time-varying default factor. Because this factor is not explained by our very rich set of controls for economic fundamentals, and it increases with the number of people in one's state who have previously filed for bankruptcy, these results are consistent with the stigma effect.

Our analysis does not identify what caused the estimated change in stigma. Indeed, the stigma and risk effects can be interrelated. It is possible, for instance, that a previous deterioration in risk-composition or economic fundamentals caused a critical mass of people to declare bankruptcy, leading in turn to the reduction in stigma that we observe. This suggests the possibility of multiple equilibria or hysteresis in default rates. Furthermore, our analysis does not provide a forecast about the future path of stigma. Nevertheless, if the drop in stigma is due to a reduction in social opprobrium or to an increase in information, it would most likely be difficult to reverse. And if stigma in turn decreases with the number of people who have defaulted, future recessions could ratchet up default rates.

This analysis can be extended in a number of ways. First, the authors are attempting to collect additional data to lengthen the sample period. Second, better predictors of default might be constructed. Evidently the credit risk scores did not fully predict the recent increase in default rates. Since variables other than the scores were also found to be significant in predicting default, the scores might not even be efficient predictors. Better predictors might improve credit risk management and lead to a more efficient allocation of credit. Further, the standard risk scores do not summarize the expected future profitability of accounts. "Profit scores" might be constructed to combine default probabilities with expected future cash flows. Third, because the estimated stigma effect represents an increase in the probability of default that is common across accounts, it would be interesting to examine its implications for portfolio diversification and securitization. Fourth, in a companion paper, Gross and Souleles (1999), the authors are investigating more generally how people use their credit cards, including how they respond to changes in credit supply like credit limits and interest rates. Understanding why people accumulate large quantities of debt in the first place should shed additional light on why some people default.

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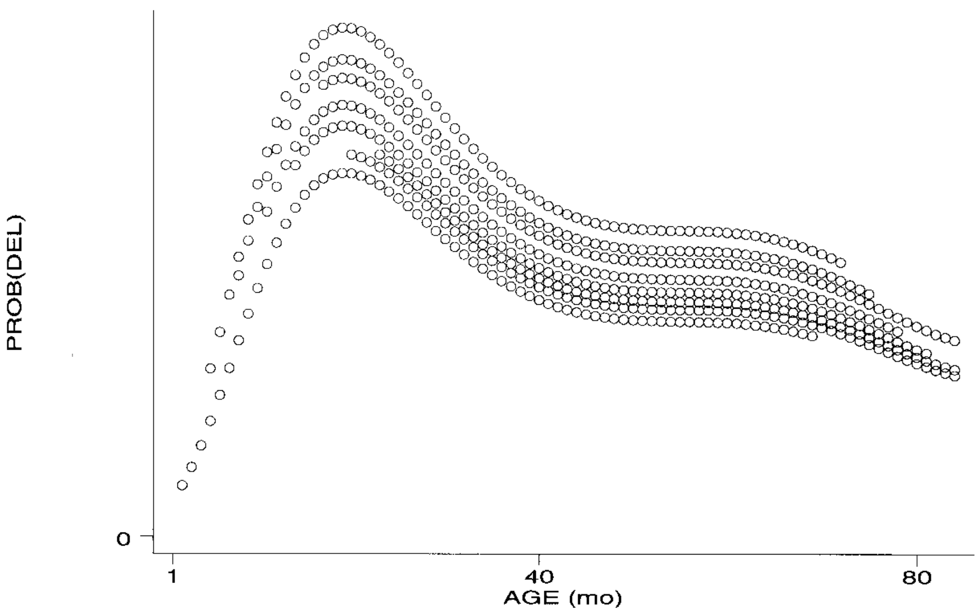

Fig. 1. The effects of account age (in months) and time on the probability of delinquency. Each curve represents the hazard function for a different quarter.

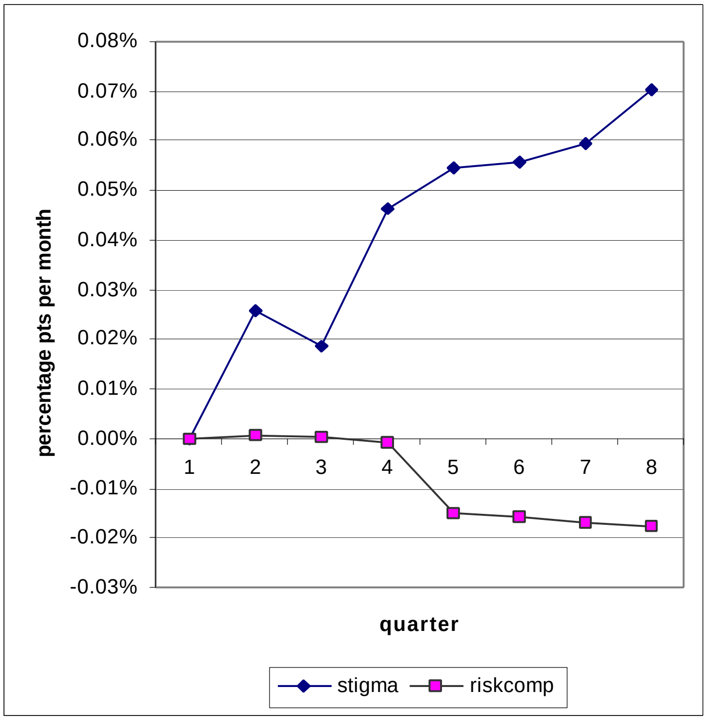

Fig. 2. Marginal effects calculated from the baseline probit model of bankruptcy.

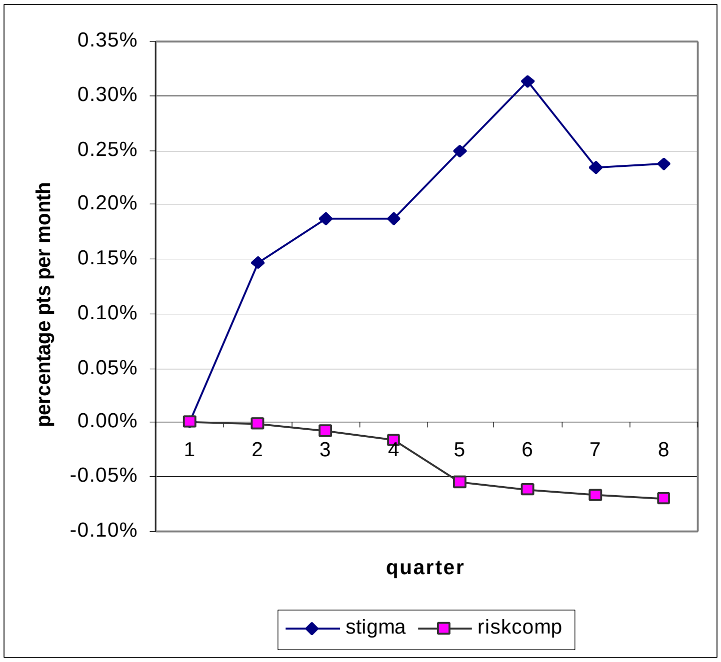

Fig. 3. Marginal effects calculated from the baseline probit model of credit card delinquency.

[Table 1 here]

Table 2: Probit Models of Bankruptcy

This table shows the results of probit models of bankruptcy (BK) using monthly credit-card account panel data from July 1995 through June 1997. The independent variables control for time effects, account age, measures of account risk, and local economic conditions. *quarter2* to *quarter8* are dummy variables for the calendar quarter. *age* to age^5 represent a fifth-order polynomial in account age. *utilization2* to *utilization7* are dummy variables for successively higher utilization rates. *line* is the credit limit, and *payments* and *purchases* are normalized by the line. *internal_score* and *external_score* are the credit risk scores. *unemployment* is the local unemployment rate, *no_insure* the fraction of people without health insurance, and *house_prices* the median real new house price. Coefficients on dummy variables for the issuer are not shown. Standard errors are corrected for heteroskedasticity and dependence within accounts. The number of observations is the number of account-months. $age^n = age^{n-1} * age/100$. $external\_score^2 = external\_score * external\_score/1000$. $internal\_score^2 = internal\_score * internal\_score /1000$.

In the baseline specification in Column (1) the risk controls are all taken from month *0*, June 1995. Column (2) interacts the polynomial in account age with the risk controls. Only the coefficients on the primary, non-interacted variables are shown. Column (3) uses the updated credit limit (once lagged). Column (4) adds dummy variables for the cardholder's state, whose coefficients are not shown. *staterate* in Column (5) is the aggregate bankruptcy rate in the state, averaged over the previous two calendar quarters.

BK	(1) baseline specification			(2) interact with age			(3) update credit line		
	coef.	s.e.	p-val	coef.	s.e.	p-val	coef.	s.e.	p-val
quarter2	0.141	0.052	0.007	0.159	0.053	0.003	0.142	0.052	0.007
quarter3	0.108	0.053	0.043	0.130	0.055	0.018	0.108	0.054	0.044
quarter4	0.220	0.055	0.000	0.246	0.057	0.000	0.221	0.055	0.000
quarter5	0.248	0.065	0.000	0.269	0.067	0.000	0.248	0.065	0.000
quarter6	0.250	0.066	0.000	0.266	0.068	0.000	0.251	0.066	0.000
quarter7	0.263	0.067	0.000	0.275	0.069	0.000	0.266	0.068	0.000
quarter8	0.293	0.069	0.000	0.307	0.070	0.000	0.297	0.069	0.000
age	0.079	0.049	0.106	-0.187	0.090	0.038	0.078	0.049	0.113
age^2	-0.486	0.282	0.084	-0.270	0.305	0.375	-0.472	0.282	0.095
age^3	1.339	0.735	0.068	1.428	0.764	0.062	1.292	0.736	0.079
age^4	-1.647	0.875	0.060	-1.635	0.904	0.070	-1.583	0.876	0.071
age^5	0.733	0.385	0.057	0.681	0.396	0.085	0.702	0.386	0.069
utilization2	0.087	0.084	0.297	0.080	0.087	0.355	0.095	0.084	0.259
utilization3	0.352	0.086	0.000	0.255	0.126	0.042	0.360	0.086	0.000
utilization4	0.335	0.093	0.000	0.203	0.149	0.174	0.344	0.093	0.000
utilization5	0.327	0.088	0.000	0.171	0.160	0.285	0.334	0.088	0.000
utilization6	0.544	0.084	0.000	0.365	0.171	0.033	0.549	0.084	0.000
utilization7	0.559	0.095	0.000	0.376	0.187	0.044	0.557	0.095	0.000
payments	-1.228	0.451	0.006	-10.203	1.924	0.000	-1.253	0.460	0.006
purchases	0.195	0.172	0.256	1.443	0.723	0.046	0.185	0.172	0.283
line	3.74e-6	5.44e-6	0.491	-3.15e-5	2.22e-5	0.157	-8.10e-6	4.82e-6	0.093
internal_score	-0.019	0.008	0.017	-0.020	0.008	0.013	-0.020	0.008	0.013
$internal\_score^2$	0.011	0.006	0.053	0.005	0.006	0.381	0.012	0.006	0.041
external_score	0.018	0.004	0.000	0.020	0.004	0.000	0.018	0.004	0.000
$external\_score^2$	-0.016	0.003	0.000	-0.016	0.003	0.000	-0.016	0.003	0.000
unemployment	5.970	1.603	0.000	5.601	1.624	0.001	6.127	1.604	0.000

no_insurance	0.059	0.354	0.867	0.035	0.357	0.923	0.062	0.354	0.861
house_prices	-2.38e-6	1.15e-6	0.038	-2.44e-6	1.15e-6	0.034	-2.26e-6	1.15e-6	0.048
# of obs		246749			246749			246749	
log likelihood		-3061.0			-3036.9			-3060.3	
pseudo R2		0.127			0.134			0.128	

Table 2 (cont)

BK	(4) state dummies			(5) state bankruptcy rate		
	coef.	s.e.	p-val	coef.	s.e.	p-val
quarter2	0.140	0.053	0.008	0.130	0.052	0.013
quarter3	0.109	0.054	0.043	0.097	0.054	0.070
quarter4	0.222	0.056	0.000	0.192	0.056	0.001
quarter5	0.258	0.068	0.000	0.194	0.067	0.004
quarter6	0.258	0.069	0.000	0.186	0.069	0.007
quarter7	0.272	0.072	0.000	0.196	0.070	0.005
quarter8	0.302	0.077	0.000	0.216	0.073	0.003
age	0.076	0.049	0.122	0.080	0.049	0.105
age^2	-0.464	0.283	0.102	-0.487	0.283	0.086
age^3	1.272	0.739	0.085	1.324	0.738	0.073
age^4	-1.561	0.879	0.076	-1.609	0.878	0.067
age^5	0.692	0.387	0.074	0.708	0.387	0.067
utilization2	0.090	0.084	0.284	0.091	0.084	0.278
utilization3	0.348	0.085	0.000	0.354	0.086	0.000
utilization4	0.327	0.092	0.000	0.337	0.093	0.000
utilization5	0.328	0.088	0.000	0.330	0.088	0.000
utilization6	0.548	0.084	0.000	0.546	0.084	0.000
utilization7	0.554	0.095	0.000	0.560	0.095	0.000
payments	-1.252	0.448	0.005	-1.258	0.455	0.006
purchases	0.219	0.168	0.194	0.196	0.170	0.250
line	6.62e-7	5.40-6	0.902	1.95e-6	5.45e-6	0.721
internal_score	-0.019	0.008	0.019	-0.018	0.008	0.026
$internal\_score^2$	0.011	0.006	0.058	0.010	0.006	0.074
external_score	0.018	0.004	0.000	0.018	0.004	0.000
$external\_score^2$	-0.016	0.003	0.000	-0.016	0.003	0.000
unemployment	4.959	5.036	0.325	4.196	1.733	0.015
no_insurance	-3.010	1.907	0.114	-0.002	0.366	0.995
house_prices	4.53e-6	1.10e-5	0.681	-1.23e-6	1.26e-6	0.326
staterate				1.00e+3	2.32e+2	0.000
$staterate^2$				-3.70e+5	9.38e+4	0.000
# of obs		246749			246749	
log likelihood		-3036.9			-3052.8	
pseudo R2		0.134			0.130	

Table 3: Marginal Effects for Bankruptcy

Each column reports the marginal effects for the probit models in the corresponding column in Table 2, as defined by Eqs. (2) and (3). $stigma_t$ shows the effect on bankruptcy rates of varying only the time dummies across quarters t, relative to the first quarter. $riskcomp_t$ shows the effect of varying account age and the economic control variables across their cross-sectional averages in different quarters. The units are in percentage points per month.

specification	(1) baseline specification		(2) interact with age		(3) update credit line	
	marginal	s.e.	marginal	s.e.	marginal	s.e.
$stigma_t$						
quarter1	0.000%		0.000%		0.000%	
quarter2	0.026%	0.010%	0.018%	0.007%	0.026%	0.010%
quarter3	0.019%	0.010%	0.014%	0.006%	0.019%	0.010%
quarter4	0.046%	0.013%	0.033%	0.009%	0.047%	0.014%
quarter5	0.055%	0.018%	0.038%	0.012%	0.056%	0.018%
quarter6	0.056%	0.018%	0.037%	0.012%	0.057%	0.019%
quarter7	0.060%	0.019%	0.039%	0.013%	0.062%	0.020%
quarter8	0.070%	0.021%	0.046%	0.014%	0.073%	0.022%
$riskcomp_t$						
quarter1	0.000%		0.000%		0.000%	
quarter2	0.001%	0.002%	0.004%	0.001%	0.001%	0.002%
quarter3	0.000%	0.003%	0.007%	0.003%	0.000%	0.003%
quarter4	-0.001%	0.004%	0.008%	0.003%	-0.001%	0.004%
quarter5	-0.015%	0.003%	-0.002%	0.003%	-0.016%	0.003%
quarter6	-0.016%	0.003%	-0.002%	0.003%	-0.017%	0.004%
quarter7	-0.017%	0.003%	-0.003%	0.003%	-0.018%	0.004%
quarter8	-0.018%	0.004%	-0.004%	0.004%	-0.019%	0.004%

specification	(4) state dummies		(5) state bankruptcy rate	
	marginal	s.e.	marginal	s.e.
$stigma_t$				
quarter1	0.000%		0.000%	
quarter2	0.023%	0.009%	0.022%	0.009%
quarter3	0.017%	0.009%	0.016%	0.009%
quarter4	0.042%	0.012%	0.037%	0.012%
quarter5	0.052%	0.017%	0.038%	0.015%
quarter6	0.052%	0.018%	0.036%	0.016%
quarter7	0.056%	0.019%	0.038%	0.016%
quarter8	0.066%	0.023%	0.044%	0.018%
$riskcomp_t$				
quarter1	0.000%		0.000%	
quarter2	0.001%	0.002%	0.002%	0.002%
quarter3	0.000%	0.003%	0.002%	0.003%
quarter4	-0.001%	0.003%	0.004%	0.004%
quarter5	-0.014%	0.003%	-0.009%	0.004%
quarter6	-0.015%	0.003%	-0.009%	0.004%
quarter7	-0.016%	0.004%	-0.010%	0.004%
quarter8	-0.016%	0.004%	-0.009%	0.005%

Table 4: Probit Models of Delinquency

This table shows the results of probit models of delinquency (DEL) using monthly credit-card account panel data from July 1995 through June 1997. The independent variables control for time effects, account age, measures of account risk, and local economic conditions. *quarter2* to *quarter8* are dummy variables for the calendar quarter. *age* to age^5 represent a fifth-order polynomial in account age. *utilization2* to *utilization7* are dummy variables for successively higher utilization rates. *line* is the credit limit, and *payments* and *purchases* are normalized by the line. *internal_score* and *external_score* are the credit risk scores. *unemployment* is the local unemployment rate, *no_insure* the fraction of people without health insurance, and *house_prices* the median real new house price. Coefficients on dummy variables for the issuer are not shown. Standard errors are corrected for heteroskedasticity and dependence within accounts. The number of observations is the number of account-months. $age^n = age^{n-1} * age/100$. $external\_score^2 = external\_score * external\_score/1000$. $internal\_score^2 = internal\_score * internal\_score/1000$.

In the baseline specification in Column (1) the risk controls are all taken from month *0*, June 1995. Column (2) interacts the polynomial in account age with the risk controls. Only the coefficients on the primary, non-interacted variables are shown. Column (3) uses the updated credit limit (once lagged). Column (4) adds dummy variables for the cardholder's state, whose coefficients are not shown.

DEL	(1) baseline specification			(2) interact with age			(3) update credit line		
	coef.	s.e.	p-val	coef.	s.e.	p-val	coef.	s.e.	p-val
quarter2	0.212	0.030	0.000	0.231	0.031	0.000	0.212	0.030	0.000
quarter3	0.254	0.032	0.000	0.277	0.033	0.000	0.257	0.032	0.000
quarter4	0.253	0.034	0.000	0.276	0.035	0.000	0.259	0.034	0.000
quarter5	0.308	0.038	0.000	0.327	0.039	0.000	0.316	0.038	0.000
quarter6	0.359	0.039	0.000	0.370	0.040	0.000	0.373	0.039	0.000
quarter7	0.297	0.041	0.000	0.305	0.041	0.000	0.317	0.041	0.000
quarter8	0.299	0.043	0.000	0.305	0.044	0.000	0.323	0.044	0.000
age	0.073	0.031	0.018	-0.093	0.055	0.089	0.075	0.031	0.015
age^2	-0.413	0.182	0.023	-0.175	0.196	0.371	-0.421	0.182	0.021
age^3	1.014	0.483	0.036	0.772	0.490	0.115	1.027	0.483	0.034
age^4	-1.114	0.583	0.056	-0.789	0.589	0.180	-1.122	0.583	0.054
age^5	0.445	0.260	0.086	0.292	0.261	0.264	0.446	0.260	0.086
utilization2	0.011	0.039	0.779	0.035	0.043	0.416	0.024	0.040	0.537
utilization3	0.042	0.044	0.330	0.107	0.067	0.114	0.056	0.044	0.202
utilization4	0.084	0.050	0.093	0.170	0.082	0.039	0.100	0.050	0.047
utilization5	0.030	0.046	0.510	0.123	0.088	0.164	0.043	0.046	0.354
utilization6	0.146	0.043	0.001	0.251	0.094	0.008	0.156	0.044	0.000
utilization7	0.203	0.052	0.000	0.322	0.105	0.002	0.208	0.053	0.000
payments	-1.189	0.171	0.000	-4.286	1.215	0.000	-1.193	0.172	0.000
purchases	0.522	0.098	0.000	0.776	0.419	0.064	0.509	0.098	0.000
line	-1.95e-5	4.19e-6	0.000	-4.51e-5	1.56e-5	0.004	-2.67e-5	3.76e-6	0.000
internal_score	-0.020	0.005	0.000	-0.016	0.005	0.002	-0.021	0.005	0.000
$internal\_score^2$	0.010	0.004	0.010	0.004	0.004	0.294	0.011	0.004	0.005
external_score	0.000	0.003	0.940	0.000	0.003	0.870	-0.001	0.003	0.810
$external\_score^2$	-0.002	0.002	0.235	-0.002	0.002	0.239	-0.002	0.002	0.337
unemployment	0.210	1.120	0.851	-0.049	1.126	0.966	0.366	1.125	0.745
no_insurance	0.606	0.253	0.017	0.590	0.251	0.019	0.606	0.254	0.017

house_prices	6.53e-7	7.49e-7	0.383	6.32e-7	7.46e-7	0.397	7.15e-7	7.53e-7	0.342
# of obs		367047			367047			367047	
log likelihood		-11990.8			-11961.2			-11971.7	
pseudo R2		0.142			0.144			0.143	

DEL	(4) state dummies		
	coef.	s.e.	p-val
quarter2	0.217	0.030	0.000
quarter3	0.262	0.032	0.000
quarter4	0.262	0.035	0.000
quarter5	0.328	0.039	0.000
quarter6	0.378	0.041	0.000
quarter7	0.319	0.045	0.000
quarter8	0.322	0.051	0.000
age	0.068	0.031	0.027
age^2	-0.389	0.182	0.033
age^3	0.967	0.485	0.046
age^4	-1.072	0.586	0.067
age^5	0.430	0.261	0.099
utilization2	0.009	0.040	0.821
utilization3	0.038	0.044	0.389
utilization4	0.084	0.050	0.095
utilization5	0.030	0.046	0.513
utilization6	0.144	0.043	0.001
utilization7	0.205	0.053	0.000
payments	-1.171	0.171	0.000
purchases	0.529	0.097	0.000
line	-2.03e-5	4.29e-6	0.000
internal_score	-0.020	0.005	0.000
$internal\_score^2$	0.010	0.004	0.009
external_score	0.000	0.003	0.928
$external\_score^2$	-0.003	0.002	0.172
unemployment	0.236	2.922	0.936
no_insurance	-0.302	1.310	0.818
house_prices	-1.26e-6	7.46e-6	0.865
# of obs	367047		
log likelihood	-11954.6		
pseudo R2	0.145		

Table 5: Marginal Effects for Delinquency

Each column reports the marginal effects for the probit models in the corresponding column in Table 4, as defined by Eqs. (2) and (3). $stigma_t$ shows the effect on delinquency rates of varying only the time dummies across quarters t, relative to the first quarter. $riskcomp_t$ shows the effect of varying account age and the economic control variables across their cross-sectional averages in different quarters. The units are in percentage points per month.

specification	(1) baseline specification		(2) interact with age		(3) update credit line	
	marginal	s.e.	marginal	s.e.	marginal	s.e.
$stigma_t$						
quarter1	0.000%		0.000%		0.000%	
quarter2	0.147%	0.022%	0.130%	0.019%	0.152%	0.022%
quarter3	0.188%	0.027%	0.168%	0.024%	0.197%	0.027%
quarter4	0.187%	0.029%	0.167%	0.025%	0.199%	0.030%
quarter5	0.249%	0.038%	0.214%	0.033%	0.266%	0.040%
quarter6	0.313%	0.045%	0.261%	0.038%	0.342%	0.048%
quarter7	0.234%	0.040%	0.193%	0.034%	0.267%	0.044%
quarter8	0.237%	0.044%	0.193%	0.036%	0.275%	0.048%
$riskcomp_t$						
quarter1	0.000%		0.000%		0.000%	
quarter2	-0.002%	0.004%	0.006%	0.003%	-0.005%	0.004%
quarter3	-0.008%	0.006%	0.008%	0.006%	-0.014%	0.006%
quarter4	-0.015%	0.007%	0.009%	0.007%	-0.024%	0.007%
quarter5	-0.055%	0.007%	-0.021%	0.007%	-0.065%	0.007%
quarter6	-0.061%	0.007%	-0.023%	0.008%	-0.075%	0.008%
quarter7	-0.066%	0.008%	-0.025%	0.009%	-0.083%	0.008%
quarter8	-0.070%	0.008%	-0.027%	0.009%	-0.089%	0.008%

specification	(4) state dummies	
	marginal	s.e.
$stigma_t$		
quarter1	0.000%	
quarter2	0.141%	0.022%
quarter3	0.181%	0.028%
quarter4	0.182%	0.030%
quarter5	0.252%	0.041%
quarter6	0.315%	0.050%
quarter7	0.242%	0.047%
quarter8	0.245%	0.055%
$riskcomp_t$		
quarter1	0.000%	
quarter2	-0.003%	0.004%
quarter3	-0.009%	0.005%
quarter4	-0.016%	0.007%
quarter5	-0.054%	0.008%
quarter6	-0.059%	0.009%
quarter7	-0.064%	0.010%
quarter8	-0.068%	0.011%