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Explaining the Increase in Bankruptcy and Delinquency: Stigma versus Risk-Composition

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Abstract

Between 1994 and 1997 the number of personal bankruptcy filings in the U.S. rose by 73%. Delinquency rates on credit cards rose almost as sharply. This paper investigates the two leading explanations for the recent increase in bankruptcy and delinquency. Under the "risk effect," less credit-worthy borrowers have recently obtained additional credit, leading to an increase in default. Under the "stigma effect," people have become more willing to default over time, even controlling for their risk characteristics and other economic fundamentals. Previous studies have been unable to distinguish these two explanations because traditional data sets cannot be used to measure the changing risk-composition of borrowers. This paper uses a new data set containing a panel of several hundred thousand individual credit card accounts from several different issuers. This data set is unique in containing a large sample of borrowers who have defaulted, as well as a rich set of measures of credit supply and borrowers' credit risk. We use this data to estimate hazard functions for consumer default, for both bankruptcy and credit card delinquency, and to assess the relative importance of different variables in predicting default. We investigate how the propensity to default has changed over time, in order to separate the risk and stigma effects.

A key finding is that even after controlling for risk-composition and other economic fundamentals, the propensity to default significantly increased between 1995 and 1997. A credit card holder in 1997 was 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. By contrast, increases in credit limits and other changes in risk composition explain only a small part of the change in default rates over time. These results are consistent with the stigma effect.

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Between 1994 and 1997 the number of personal bankruptcy filings in the U.S. rose by 73%. The 1.35 million filings in 1997 represent well over 1% of U.S. households. Delinquency rates on credit cards have risen almost as sharply.[1] These trends in default, both in bankruptcy and delinquency, are particularly surprising in light of the strong economy over the period. The resulting losses to lenders represent a sizeable fraction of the interest payments they collect, potentially raising the average cost of credit.

There are two leading explanations 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.[2]

A second explanation for these trends is a decline in the social stigma associated with default or an increase in knowledge about default. Under the "stigma effect," people have become more willing to default over time, even controlling for their risk characteristics and other economic fundamentals. Even a relatively small decline in stigma can potentially have large effects. For example, White (1997) calculated that between 15% and 31% of U.S. households could benefit, in terms of their current net worth, by filing for bankruptcy. If the decline in stigma caused even a small fraction of these households to file, default rates would substantially increase.

It is important to determine the relative significance of these alternative explanations. For example, some policy makers have advocated restricting credit supply in order to improve the risk composition of the borrowing population. Others have advocated making the terms of bankruptcy less attractive in order to increase the perceived costs of default. However, it has been difficult to separate the risk and stigma effects empirically. First, it is not obvious how to operationalize the idea of stigma to begin with. Most of the proxies for stigma that have been suggested run into problems of endogeneity and reverse causality.[3] A second difficulty is that controlling for risk-composition requires measures of credit supply and credit risk for a large sample of borrowers,

[1] Federal Reserve Board of Cleveland (1998).

[2] See for example The New York Times (1998).

[3] 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 bankruptcies could be due to the risk effect, with lawyers responding to the increased demand for their services by additional advertising.

including a large number of borrowers who have defaulted. None of the traditional household surveys provides such information. A third difficulty, to be explained below, is that the most natural econometric specification of the risk and stigma effects turns out not to be identified.

This paper uses a new data set containing a panel of several hundred thousand individual credit card accounts from several different credit card issuers.[4] 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 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 estimate hazard functions for consumer default, for both bankruptcy and credit card delinquency, and to assess the relative importance of different variables in predicting default. We investigate how the propensity to default has changed over time, in order to separate the risk and stigma effects. Since the data includes the information that the card issuers themselves use to measure risk, we are able to control for all changes in risk composition that were observable by the issuers. A key finding is that even after controlling for risk-composition and other economic fundamentals, the propensity to default significantly increased between 1995 and 1997. A credit card holder in 1997 was 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 credit card holders had become one standard deviation riskier between 1995 and 1997, 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. These results are consistent with the stigma effect.

Section I of the paper describes the data used in the analysis and Section II discusses related studies. Section III develops the econometric methodology and Section IV reports the results. Conclusions appear in Section V.

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[4] In a companion paper, Gross and Souleles (1998), we use the same panel data set to examine how people normally use their credit cards, when they do not default. We document the importance of credit cards as a source of credit for many households, with well over half of accounts not paying off their entire balance and incurring interest charges.

I. 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 a representative sample 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 all credit card accounts in the U.S. in 1995.[5] 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 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 presented 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 a partial list of the data available from most of the issuers, and their frequency.

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 investigate dynamics and control for individual fixed effects. 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. However, there is no information about some important variables like household assets or employment status.[6]

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[5] As a check, the data were benchmarked against the more limited 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.

[6] Nonetheless, the study by Fay, Hurst, and White (1998) discussed below found that the effects of such variables on bankruptcy are relatively small in magnitude.

II. 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.[7] 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 1920's and 1960's. 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 document 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 (1997) 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.[8] 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

[7] For a review see Hynes (1998).

levels) that would be relinquished. As an inverse proxy for stigma in each state, the authors use the lagged bankruptcy rate in that state. 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.[9] Second, the PSID does not contain explicit measures of household credit risk like risk scores, nor measures of credit supply like credit lines.[10]

III. Econometric Methodology

From the data set described in Section I, we drew a representative sample of all credit card accounts open as of June 1995.[11,12] 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 rise in default at the national level. Two indicator variables were created that identify the first month, if any, that an account defaulted. The delinquency indicator, DEL, identifies the first time within the sample period 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 card holder filed for bankruptcy. Accounts that are both delinquent and bankrupt are counted as bankrupt. This yields over four thousand accounts going bankrupt, and almost fifteen thousand accounts going delinquent. Accounts that never default within the sample period are included as a control

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8 The SCF subsample used in their analysis contains about 1900 households. Even at today's bankruptcy rate of approximately 1%, which is much larger than the 1983 rate, the subsample would include only about 19 households that actually filed for bankruptcy.

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

10 This complicates the study's interpretation of the lagged state bankruptcy rate as stigma. Changes in these variables, or in other aspects of risk-composition, can induce positive serial correlation in a given state's bankruptcy rate, which might be incorrectly identified as being due to stigma.

11 This sample includes all accounts in good standing as of June 1995. Accounts that had been closed or frozen on or before June 1995 because they were three or more cycles delinquent are excluded.

12 To simplify the analysis of the age of a credit card account below, the main sample 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.

group. The delinquent and the bankrupt accounts are each separately compared to the non-default control group.

For either the delinquency or bankruptcy sample, let $D_{i,t}$ indicate whether account *i* defaulted in month *t*, and $D^*_{i,t}$ be the corresponding latent index value.[13] As a first step, it will be helpful to consider the following simple specification:

$$D^*_{i,t} = \boldsymbol{a_0}'\boldsymbol{time_t} + a_1 age_{i,t} + \boldsymbol{a_2}'\boldsymbol{coh_i} + e_{i,t}\,. \quad (1)$$

$\boldsymbol{coh_i}$ is a vector of "cohort" or vintage dummy variables representing the time at which account *i* was opened. For example, the 1990 cohort includes the accounts that were opened in 1990. These cohort dummies allow for the possibility that more recent cohorts are more likely to default than older cohorts, *ceteris paribus*. This could happen for instance if lending standards became looser over time. The variable $age_{i,t}$ represents the number of months that account *i* has been open by time *t*. This variable allows for "seasoning" of credit card portfolios: for any given cohort, accounts might be more (or less) likely to default soon after opening than in later years. $\boldsymbol{coh_i}$ and $age_{i,t}$ control for two different aspects of the risk-composition of each account: a fixed component and the variable, hazard-rate component. The time dummies, grouped by calendar quarter, allow for changes over time in the propensity to default, for accounts of all ages and cohorts. These time dummies will later be identified with the stigma effect.[14]

Identification of even this simple specification is complicated by the "life-cycle" identity that links the month in which an account is opened (represented by cohort), the age of the account, and the current month. Since the opening date plus age equals time, only two of the three variables in equation (1) can be included in the empirical specification, and even then, the two included variables may be picking up the effects of the omitted third variable. Figures 1 and 2 illustrate the resulting identification problem. A probit model of delinquency was first estimated with only the time dummies and a fifth-order polynomial in account age as independent variables,

[13] For example, 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. An account which never goes three cycles delinquent would have D_{it}=0 for the entire sample or until it closes in good standing.

[14] In contrast to this dynamic specification of consumer default, much of the analysis of corporate default uses static, cross-sectional specifications. See Shumway (1998).

omitting the cohort dummies. Figure 1 shows the predicted values. Each curve shows the effect of age on delinquency, essentially a non-parametric hazard function, for a different quarter. The age effects are statistically significant and large in magnitude. Accounts are most likely to go delinquent when they are about two years old. The time dummies are also significant, implying that the hazard functions shift over time.

It is tempting to interpret the shifts in the hazard functions in Figure 1 as reflecting changes in stigma. However, because of the identification problem, the quarter dummies may not only pick up the effects of time. Instead, they might also be capturing cohort effects. Figure 2 shows the results of another probit model of delinquency, with independent variables the same quintic polynomial in account age, but this time replacing the quarter dummies with cohort dummies. Each curve in the figure now represents the age hazard for a given cohort, over the period in which that cohort appears in the sample.[15] The effect of age is similar to that in Figure 1, with the hazard rate peaking at about two years. But for a given age, the younger cohorts are much more likely to go delinquent than the older cohorts. Coupled with the fact that there are more accounts in the younger cohorts since card portfolios have been growing over time, this change in risk-composition can potentially explain the recent rise in default, with account age and cohort together accounting for risk-composition. For instance, the default rate might have increased in 1997 because the large and relatively risky 1995 cohort hit its two-year birthday in 1997. However, because of the identification problem, the risk-composition effect suggested by Figure 2 is observationally equivalent to the stigma effect suggested by Figure 1. Even with panel data it is inherently difficult to distinguish the two effects.[16]

However, it is possible to avoid the identification problem by using risk data from individual accounts. We assume that the reason that different cohorts have different probabilities of default is that there are different numbers of risky accounts in each cohort. Since what matters

[15] The cohort dummies are for 1990, 1991, 1992, the first and second halves of 1993 and 1994, and the first half of 1995. The curve furthest to the south-east represents the 1990 cohort, which was already over 50 months old at the beginning of the sample in 1995 and is then followed for the 24 months of the sample period. The curve furthest to the west represents accounts opened in the first part of 1995, which are only a few months old at the start of the sample and are also followed for the 24 months of the sample period.

[16] To make the difficulty clearer, consider the following example. Suppose one observes that the 1995 cohort had a greater default rate when it was 2 years old (in 1997) than the 1990 cohort had when it was 2 years old (in 1992). This could be due to a cohort effect, if the 1995 cohort was riskier, at any age, than the 1990 cohort, as in Figure 2. Alternatively, this could be due to a time effect, if all accounts in 1997 were more likely to default than were accounts in 1992, whatever their cohort and age.

is the riskiness of the individual accounts, the cohort dummies in equation (1) can be replaced by account-specific measures of risk, $\boldsymbol{risk_{i,t}}$:

$$D^*_{i,t} = \boldsymbol{b_0}'\boldsymbol{time}_t + \boldsymbol{b_1}'\boldsymbol{age}_{i,t} + \boldsymbol{b_2}'\boldsymbol{risk}_{i,t} + \boldsymbol{b_3}'\boldsymbol{econ}_{i,t} + h_{i,t} \,. \tag{2}$$

The available risk measures are very 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 summary of the riskiness of each account. The specification also includes a vector of controls for local economic conditions, $\boldsymbol{econ_{i,t}}$, such as the state unemployment rate (*unemp*), the fraction of people in the state without health insurance (*noinsure*), and the median real new house price in the region (*house*).[17] The vector $\boldsymbol{age}_{i,t}$ represents a fifth-order polynomial in age, measured in months.

The age polynomial and the risk variables together control for the risk-composition of credit card accounts and therefore for the risk effect. The time dummies capture changes over time in the average propensity to default that are not due to risk-composition or other economic fundamentals, and are therefore assumed to capture the stigma effect. 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, equation (2) already contains a much richer set of controls than is available in the data used in previous studies. These 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 must have improved over the sample period and therefore should not lead to increases in default rates.

There are multiple possible timing conventions that could be used for the risk controls $\boldsymbol{risk}_{i,t}$ in equation (2). Since these variables were originally introduced as replacements for the fixed cohort dummies in equation (1), 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.[18]

Instead, for the main results the risk controls are taken from June 1995, the month before the start of the sample period (that is, month $t=0$). We use $\boldsymbol{risk}_{i,0}$ in equation (2) to control for the fixed component of the risk-composition of accounts. Then, to test for the risk effect, we will check whether the trends in default can be explained by more recent cohorts entering the risky part of their life cycle (*e.g.* their two-year birthday). 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.

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 may 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 $\boldsymbol{risk}_{i,t}$ is, however, 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.[19] 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.[20]

Another way in which credit supply changes during the sample period is along the extensive margin, through the introduction of new accounts. Since our sample is representative of accounts already open in June 1995, it does not include accounts which opened subsequently, during the sample period. Hence the results do not include the contribution of these youngest

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[17] While *unemp* is available monthly, *house* is measured quarterly and *noinsure* only annually. Monthly values for the latter two variables were calculated via linear interpolation. *unemp* and *noinsure* are measured in terms of tenths of a percentage point (*e.g*., *unemp* = 53 denotes an unemployment rate of 5.3%.)

[18] Also, most issuers did not store all of the application variables, especially for the older cohorts.

[19] 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. The companion paper, Gross and Souleles (1998), explicitly examines the endogeneity in the supply of credit, and cardholder response.

[20] Note that under any of the timing conventions, the risk controls incorporate some supply effects (*e.g.*, issuers' decisions to offer credit to different risk groups) and some demand effects (*e.g.*, people's decisions to open an account and how much to borrow). Thus, the estimated risk effect represents an upper bound on the effects of issuer supply decisions.

accounts to national default rates between mid 1995 and mid 1997. However, this should not be a problem for our analysis. The results will fully capture the contribution of the risk-composition of the accounts that are in the sample, to the default rates in the sample. Moreover, if the model is correctly specified, so that stigma is independent of account age and risk characteristics, new accounts should have no effect on the estimated values for stigma. While new accounts could change estimated risk-composition effects, the difference is unlikely to explain the aggregate trends in default, since the flow of new accounts during the sample period represents only a relatively small part of the initial stock of accounts.

Both probit and logit models of equation (2) were estimated. Because the results were both qualitatively and quantitatively similar, we usually report only the probit results. The standard errors allow for heteroscedasticity and serial correlation within accounts. Dummy variables for the issuers are included but not reported. Various extensions of equation (2) 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 equation (2) 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

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

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.

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

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 economic fundamentals, we include in *riskcomp* the effects of changes in economic conditions, by varying ***econ***. Second, since $\boldsymbol{risk}_{i,0}$ controls for the fixed component of each account's risk, it does not contribute to variation in risk-composition over the sample period. As a result the changes in $riskcomp_t$ over time are all due to changes in the variable component of risk-composition, $\boldsymbol{age}_{i,t}$, and in $\boldsymbol{econ}_{i,t}$. 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.

IV. Results

Table 2 shows the main 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. The unemployment rate *unemp* and house prices *house* are significant with the expected signs: greater unemployment and weaker housing prices are associated with more bankruptcies. The risk controls are individually and jointly very significant. Two risk scores are included. 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. Both credit scores are highly significant with 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. *util1* to *util7* represent a utilization rate of 0, in (0,.4], (.4,.7], (.7,.8], (.8,.9], and (.9,1.0], and over 1.0, respectively. Not surprisingly, accounts with higher utilization rates are more likely to go bankrupt. Accounts making smaller payments or larger purchases also go bankrupt more often, although the latter effect is not significant.[21] The coefficient on the line is insignificant, but will be discussed further below. The age variables remain jointly significant although the associated age hazard function is less sharply peaked than in Figure 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. Stigma appears to have declined, even after controlling for the risk-composition of accounts.

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 the second panel of Table 2, and are graphed in Figure 3. $riskcomp_t$ initially rises, but only slightly, and then declines. Since the temporal variation in $riskcomp_t$ is due to changes in $\boldsymbol{age}_{i,t}$ and $\boldsymbol{econ}_{i,t}$, the aging of the portfolio and improvements in economic conditions actually imply some decrease in the bankruptcy rate over time. The time dummies effectively capture the difference between this implied bankruptcy rate and the actual rate. The magnitudes for $stigma_t$ are much larger than those for $riskcomp_t$ and are statistically and economically significant. The probability of bankruptcy in quarter eight is about 0.09 percentage points per month larger than at the start of the sample. At an annual rate this translates into 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

[21] Since variables other than the credit scores are statistically significant, the scores might not represent an optimal measure of the probability of default.

increase in the internal risk score raises the average probability of bankruptcy by about 0.07 percentage points per month. Note that the marginal value of $stigma_t$ in quarter eight is even larger than this. Thus, the estimated stigma effect increased the bankruptcy rate by even more than would have resulted had the entire portfolio become one standard deviation riskier – again a substantial effect.[22]

Table 3 presents some extensions of this analysis for bankruptcy. Column (1) shows the effects of interacting all of the risk controls $\boldsymbol{risk}_{i,0}$ with the age polynomial. This interaction essentially allows each risk group to have its own nonparametric hazard function. The table shows the resulting coefficients on the primary, non-interacted variables, with the associated marginal values. The interaction terms are significant for payments, the line, and the two risk scores. Nonetheless, the coefficients on the time dummies show little change. Their associated marginal values $stigma_t$ have decreased by over 1/3 in magnitude, but they retain their original pattern from Table 2. The marginal values $riskcomp_t$ peak in quarter 4, but now remain positive. Although initially significant, they remain small in magnitude and still much smaller than $stigma_t$.

Column (2) of Table 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 becomes significant, but negative, implying that larger lines are associated with less default. This reflects the endogeneity of the line: 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 (3) of Table 3 extends the analysis to a conditional logit model with a fixed effect by zip code. This fixed effect controls for all persistent geographical effects on the propensity to default. For instance, additional credit might have recently been obtained by riskier households living in poorer areas. Similarly, state regulations, judicial attitudes, average household demographics, and the average level of the social stigma of default may all differ across regions. Adding the fixed effect does not change the qualitative pattern of the results. In particular, the

[22] We similarly computed the effects of varying other risk controls. The values for stigma are always large in comparison.

coefficients on the quarter dummies remain significant and rise monotonically. The conditional logit results remain similar on interacting the risk controls with age or using the updated credit line.

The same analysis was undertaken using delinquency as the indicator of default. Table 4 presents the main results. The pattern of coefficients on the risk controls is similar to that in Table 2 for bankruptcy. Now *noinsure* is significant, with lack of insurance associated with more delinquency. Once again people with larger balances and lower risk scores are much more likely to default. Even with these controls for risk, the coefficients on the time dummies are again highly significant. This time they rise sharply for six quarters and then plateau. Figure 4 graphs the corresponding marginal values. The magnitudes of $stigma_t$ are again much larger than for $riskcomp_t$, which again turns negative. The magnitudes of $stigma_t$ are also larger than in Figure 3 for bankruptcy, but this is because delinquency is much more common than bankruptcy. The peak value in quarter six of about 0.34 translates into a 4 percentage point increase in the annual delinquency rate. For comparison, increasing all 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 the stigma effect is weaker for delinquency than for bankruptcy.

Table 5 presents some extensions of the analysis for delinquency. Column (1) shows the results on interacting $\boldsymbol{risk}_{i,0}$ with age. This time the interaction terms for purchases and the two 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. The marginal values $riskcomp_t$ again increase, compared to Table 4, though they still turn negative and remain small in magnitude. Column (2) reports the results on using the updated credit line $line_{i,t-1}$. The coefficient on the line is again negative and highly significant. As reported in Column (3), adding a fixed effect by zip code yields coefficients for the time dummies that are now monotonically increasing through all eight quarters.

For both bankruptcy and delinquency, some additional risk controls were added to equation (2), 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 number of bankcards and total debt normalized by income. While such variables are generally significant, the coefficients on the time dummies always remain significant and increasing. 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.

V. Conclusion

This paper has used a unique new panel data set of credit card accounts to estimate hazard functions for consumer default and to assess the relative importance of different variables in predicting default. We investigated how the propensity to default has changed over time, in order to separate 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 are 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. Nonetheless, they explain only a small part of the change in bankruptcy and delinquency rates between 1995 and 1997. In sum, neither the risk-composition of accounts nor economic conditions changed enough to account for the variation in default rates within the sample.

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 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 credit card holders had become one standard deviation riskier between 1995 and 1997, as measured by risk scores. Overall, these results are consistent with the view that most of the recent increase in default is due to a decline in stigma. Given the large number of people who could potentially benefit from filing for bankruptcy, even relatively small drops in stigma can generate large effects on default.

Of course 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. These possibilities might argue for legal changes to increase the perceived costs of default.

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 risk scores were also found to be significant in predicting default, the scores might not even be efficient predictors. Better predictors might improve the evaluation of the credit risk that lenders undertake and lead to a more efficient allocation of credit. Further, the standard risk scores do not summarize the expected future profitability of accounts. "Revenue scores" can be constructed which combine default probabilities with expected future cash flows. Third, in a companion paper, Gross and Souleles (1988), 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.

Finally, more structural models of credit supply and demand can be constructed and calibrated. The results of this paper and the companion paper suggest a number of features that should be incorporated into such models. For instance, the unused line of credit can serve as a precautionary buffer; the credit line and interest rate are endogenous functions of past borrowing behavior; consumers have the option to default but at the cost of restricting their future access to credit; and there are wedges between the marginal costs of cash and credit making them imperfect substitutes in transactions.[23] These models could be used to analyze out-of-sample experiments

[23] Gross (1997) examined theoretically and empirically how the possibility of bankruptcy combined with differential costs of various forms of finance affected the decisions of firms. Firms were found to hold precautionary buffer stocks of liquid assets and to have different marginal propensities to invest depending upon their liquidity.

like changes in bankruptcy law. They could also be used to quantify the benefits to consumers of a flexible line of credit.[24]

[24] Jappelli, Pischke, and Souleles (1998) looked at this issue in reduced form. The consumption of households with credit cards was found to be less sensitive to income fluctuations than the consumption of households without credit cards. That is, credit cards help households "smooth" their consumption.

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Figure 1: The Effects of Account Age on Delinquency
Each curve represents a different time period (quarter).

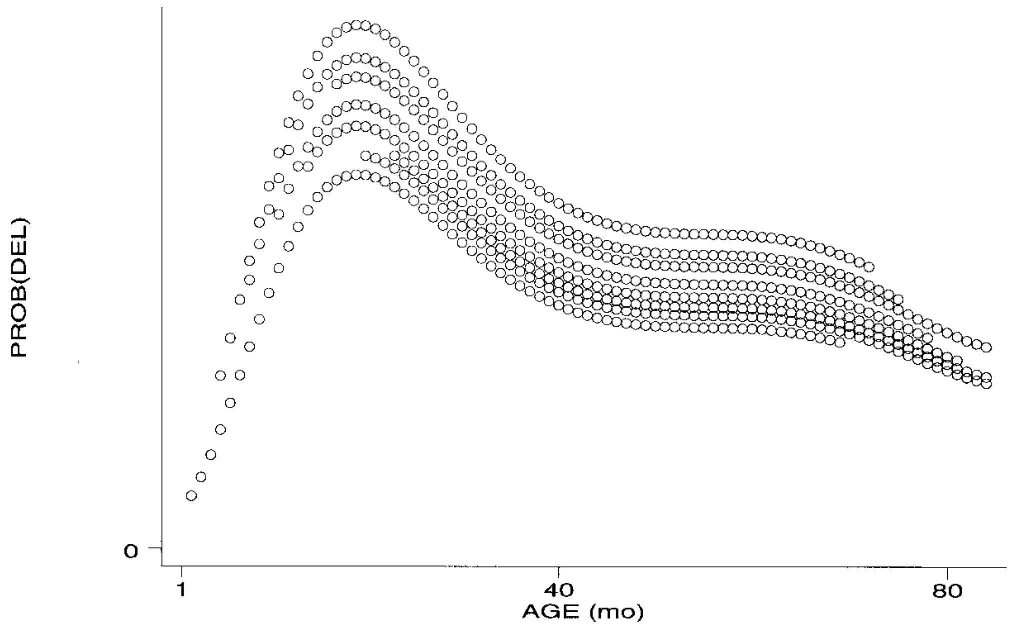

Figure 2: The Effects of Account Age on Delinquency
Each curve represents a different cohort (date account opened).

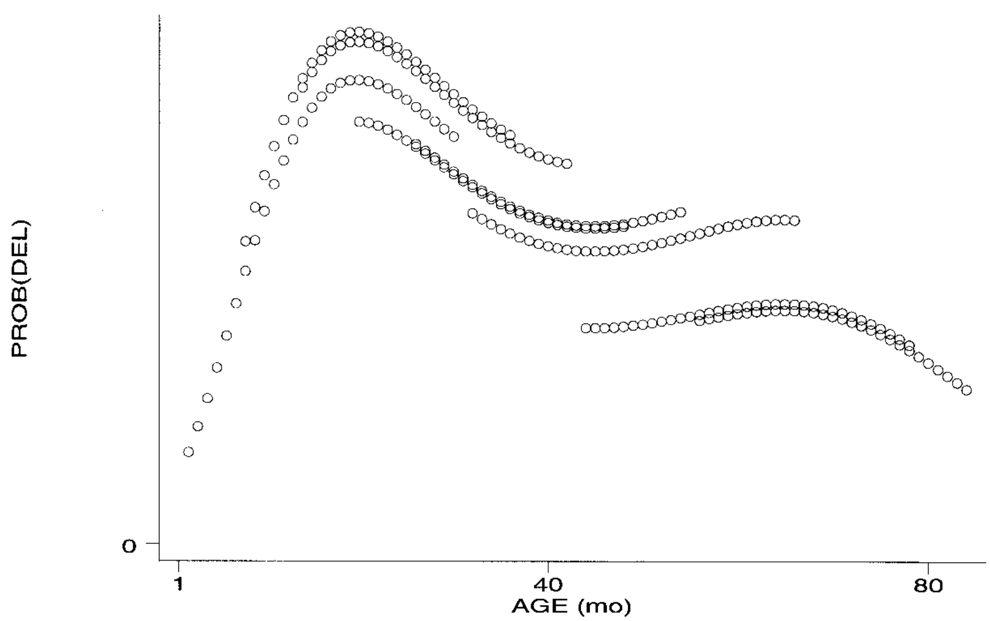

Figure 3: Marginal Effects for Bankruptcy

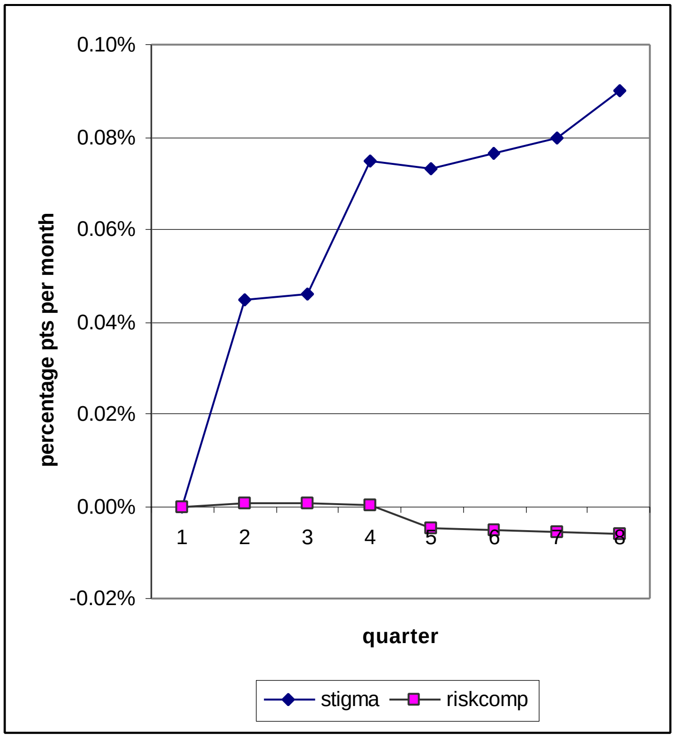

Figure 4: Marginal Effects for Delinquency

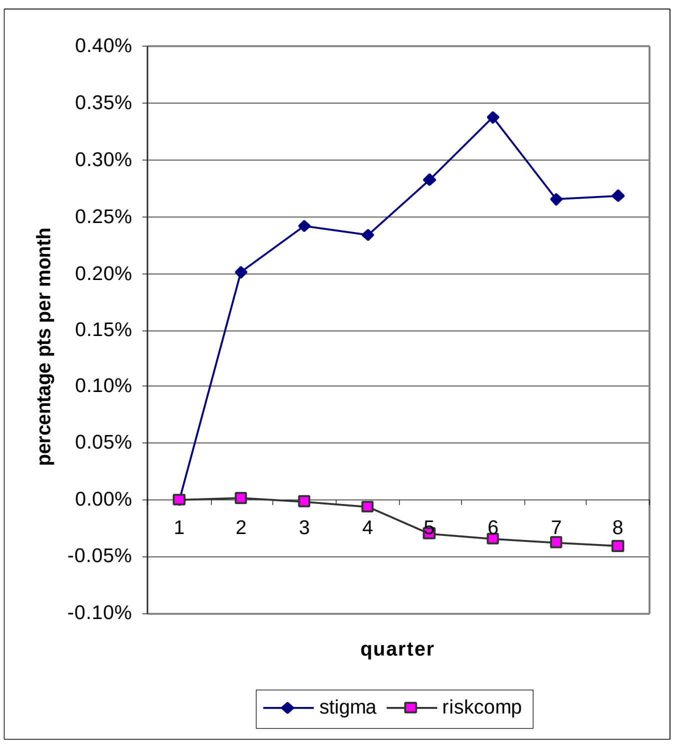

Table 1: Partial List of Available Data

Monthly
total purchases
total payments
balance
credit line
interest rate(s)
internal risk score
internal delinquency status
Periodic
number of other bank cards
balances on other bank cards
credit line on other bank cards
other credit balances
external risk score
external delinquency indicators
Once
age of cardholder
account opening date
zip code
income
type of account/features

Table 2: Probit Model of Bankruptcy

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

BK	Coef	Standard Error	z
qtr2	0.386816	0.07035	5.50
qtr3	0.392743	0.07228	5.43
qtr4	0.506351	0.07465	6.78
qtr5	0.501159	0.08380	5.98
qtr6	0.512412	0.08486	6.04
qtr7	0.522599	0.08585	6.09
qtr8	0.552988	0.08691	6.36
age	0.093485	0.05296	1.77
age^2	-0.562393	0.30154	-1.87
age^3	1.531348	0.77799	1.97
age^4	-1.874219	0.91672	-2.04
age^5	0.833227	0.39974	2.08
util2	0.063276	0.08519	0.74
util3	0.342173	0.08596	3.98
util4	0.316053	0.09198	3.44
util5	0.317393	0.08776	3.62
util6	0.522603	0.08381	6.24
util7	0.500619	0.09633	5.20
line	2.72E-06	5.58E-06	0.49
pmt/line	-0.949580	0.33132	-2.87
pur/line	0.194416	0.17015	1.14
int_score	-0.002698	0.00040	-6.75
ext_score	0.019057	0.00427	4.46
ext_score2	-0.001711	0.00032	-5.27
unemp	0.006680	0.00166	4.03
noinsure	7.34E-06	0.00036	0.02
house	-3.17E-06	1.17E-06	-2.71
# of Obs	241491		
Log Lik	-2768.20		
Pseudo R2	0.1211		

Marginal Effects (percentage points per month)

quarter	stigma	s.e.	riskcomp	s.e.
qtr1	0.000%		0.000%	
qtr2	0.044%	.0094%	0.001%	8.74e-4%
qtr3	0.045%	.0098%	0.001%	.0013%
qtr4	0.074%	.0143%	0.000%	.0015%
qtr5	0.073%	.0172%	-0.005%	.0013%
qtr6	0.076%	.0186%	-0.005%	.0014%
qtr7	0.079%	.0194%	-0.006%	.0014%
qtr8	0.089%	.0211%	-0.006%	.0015%

Notes:

- The risk controls are all taken from month 0. Coefficients on issuer dummies are not shown.
- Standard errors are corrected for general heteroskedasticity and serial correlation by account.
- $age^n = age^{n-1}$*age/100. ext_score2 = ext_score*ext_score/1000.
- The marginal effects for time (stigma) and risk (riskcomp) are computed as described in the text

Table 3: Probit Model of Bankruptcy Extensions

BK	Interact with Age (1)			Update Credit Line (2)			Fixed Effect (3)		
	Coef	Standard Error	z	Coef	Standard Error	z	Coef	Standard Error	z
qtr2	0.396	0.071	5.6	0.388	0.070	5.5	1.857	0.118	15.8
qtr3	0.406	0.074	5.5	0.393	0.072	5.4	2.680	0.129	20.8
qtr4	0.526	0.076	6.9	0.508	0.075	6.8	3.385	0.137	24.8
qtr5	0.517	0.085	6.1	0.503	0.084	6.0	3.858	0.149	26.0
qtr6	0.527	0.086	6.1	0.515	0.085	6.1	4.334	0.155	27.9
qtr7	0.534	0.087	6.1	0.528	0.086	6.1	4.861	0.163	29.9
qtr8	0.565	0.088	6.4	0.560	0.087	6.4	5.493	0.173	31.8
age	0.527	0.986	0.5	0.091	0.053	1.7	0.186	0.123	1.5
age^2	-4.158	5.698	-0.7	-0.545	0.302	-1.8	-0.633	0.669	-0.9
age^3	12.749	15.014	0.8	1.476	0.780	1.9	1.109	1.678	0.7
age^4	-17.075	18.060	-0.9	-1.801	0.919	-2.0	-1.079	1.949	-0.6
age^5	8.250	8.011	1.0	0.799	0.401	2.0	0.454	0.846	0.5
util2	-1.6E-3	9.6E-2	0.0	0.072	0.085	0.8	0.488	0.201	2.4
util3	0.058	0.163	0.4	0.351	0.086	4.1	1.524	0.203	7.5
util4	-0.073	0.201	-0.4	0.327	0.092	3.6	1.706	0.221	7.7
util5	-0.135	0.219	-0.6	0.324	0.088	3.7	1.671	0.211	7.9
util6	0.009	0.240	0.0	0.528	0.084	6.3	2.414	0.201	12.0
util7	-0.040	0.259	-0.2	0.499	0.096	5.2	2.614	0.233	11.2
line	1.1E-4	1.0E-4	1.0	-1.1E-5	4.9E-6	-2.2	4.3E-5	1.5E-5	3.0
pmt/line	-27.178	13.085	-2.1	-0.970	0.339	-2.9	-2.743	0.382	-7.2
pur/line	0.948	2.012	0.5	0.183	0.171	1.1	0.044	0.354	0.1
int_score	1.1E-3	8.6E-3	0.1	-2.6E-3	4.0E-4	-6.6	-0.015	0.001	-13.7
ext_score	0.017	0.009	1.9	0.019	0.004	4.5	0.093	0.010	9.0
ext_score2	-1.7E-3	3.2E-4	-5.4	-1.7E-3	3.2E-4	-5.2	-8.1E-3	8.0E-4	-10.2
unemp	6.4E-3	1.7E-3	3.8	6.9E-3	1.7E-3	4.2	1.9E-3	8.0E-3	0.2
noinsure	-9.1E-7	3.6E-4	0.0	1.2E-5	3.6E-4	0.0	-2.8E-3	4.3E-3	-0.6
house	-3.1E-6	1.2E-6	-2.6	-3.0E-6	1.2E-6	-2.6	-6.1E-5	2.4E-5	-2.5
# of Obs		241491			241491			110394	
Log Lik		-2747.25			-2766.77			-9132.05	
Pseudo R2		0.1277			0.1215			0.2389	

Marginal Effects (percentage points per month)

	Interact with Age (1)				Update Credit Line (2)			
Quarter	stigma	s.e.	riskcomp	s.e.	stigma	s.e.	riskcomp	s.e.
qtr1	0.000%		0.000%		0.000%		0.000%	
qtr2	0.023%	.0067%	0.002%	8.6e-4%	0.040%	.0097%	0.001%	8.8e-4%
qtr3	0.024%	.0068%	0.003%	.0015%	0.047%	.0101%	0.001%	.0013%
qtr4	0.041%	.0107%	0.004%	.0021%	0.077%	.0147%	0.000%	.0015%
qtr5	0.039%	.0119%	0.003%	.0028%	0.075%	.0177%	-0.005%	.0013%
qtr6	0.040%	.0126%	0.001%	.0019%	0.070%	.0193%	-0.006%	.0013%
qtr7	0.042%	.0130%	0.001%	.0020%	0.083%	.0203%	-0.006%	.0015%
qtr8	0.048%	.0141%	0.001%	.0021%	0.094%	.0223%	-0.007%	.0016%

Notes: See Table 2. Interaction terms in (1) are not shown.

Table 4: Probit Model of Delinquency

$$D^*_{i,t} = \boldsymbol{b_0}'\boldsymbol{time}_t + \boldsymbol{b_1}'\boldsymbol{age}_{i,t} + \boldsymbol{b_2}'\boldsymbol{risk}_{i,t} + \boldsymbol{b_3}'\boldsymbol{econ}_{i,t} + h_{i,t}$$

DEL	Coef	Standard Error	z
qtr2	0.346136	0.03348	10.34
qtr3	0.389478	0.03516	11.08
qtr4	0.380647	0.03718	10.24
qtr5	0.426408	0.04083	10.44
qtr6	0.472546	0.04187	11.29
qtr7	0.411833	0.04347	9.47
qtr8	0.413966	0.04620	8.96
age	0.066599	0.03412	1.95
age^2	-0.353702	0.19814	-1.79
age^3	0.827886	0.51971	1.59
age^4	-0.873907	0.62182	-1.41
age^5	0.335496	0.27510	1.22
util2	0.014767	0.04022	0.36
util3	0.037753	0.04334	0.87
util4	0.069884	0.04959	1.40
util5	0.021182	0.04576	0.46
util6	0.137602	0.04309	3.19
util7	0.182910	0.05319	3.43
line	-1.87E-05	4.21E-06	-4.45
pmt/line	-1.119165	0.16283	-6.87
pur/line	0.535318	0.10022	5.34
int_score	-0.006204	0.00027	-23.08
ext_score	-0.003285	0.00019	-17.54
unemp	-4.19E-05	0.00114	-0.04
noinsure	6.13E-04	0.00026	2.39
house	6.24E-07	7.50E-07	0.83
# of Obs	360840		
Log Lik	-11366.33		
Pseudo R2	0.1362		

Marginal Effects (percentage points per month)

quarter	Stigma	s.e.	riskcomp	s.e.
qtr1	0.000%		0.000%	
qtr2	0.200%	.0209%	0.001%	.0028%
qtr3	0.242%	.0261%	-0.001%	.0043%
qtr4	0.233%	.0279%	-0.005%	.0050%
qtr5	0.281%	.0360%	-0.030%	.0050%
qtr6	0.337%	.0418%	-0.033%	.0052%
qtr7	0.265%	.0378%	-0.037%	.0055%
qtr8	0.268%	.0412%	-0.040%	.0058%

Notes: See Table 2.

Table 5: Probit Model of Delinquency Extensions

DEL	Interact with Age (1)			Update Credit Line (2)			Fixed Effect (3)		
	Coef	Standard Error	z	Coef	Standard Error	z	Coef	Standard Error	z
qtr2	0.373	0.035	10.7	0.346	0.033	10.4	1.353	0.045	30.1
qtr3	0.422	0.037	11.4	0.392	0.035	11.2	1.833	0.049	37.2
qtr4	0.415	0.039	10.6	0.386	0.037	10.4	2.165	0.053	40.7
qtr5	0.455	0.042	10.8	0.434	0.041	10.7	2.639	0.058	45.4
qtr6	0.499	0.043	11.5	0.486	0.042	11.6	3.112	0.062	50.5
qtr7	0.436	0.045	9.8	0.432	0.043	10.0	3.508	0.066	52.8
qtr8	0.436	0.047	9.2	0.438	0.046	9.5	3.823	0.073	52.7
age	-0.583	0.526	-1.1	0.069	0.034	2.0	0.281	0.049	5.8
age^2	2.069	3.238	0.6	-0.362	0.198	-1.8	-1.448	0.281	-5.2
age^3	-3.350	8.995	-0.4	0.841	0.520	1.6	3.335	0.736	4.5
age^4	2.348	11.295	0.2	-0.881	0.622	-1.4	-3.575	0.885	-4.0
age^5	-0.489	5.195	-0.1	0.336	0.275	1.2	1.446	0.395	3.7
util2	0.053	0.046	1.2	0.028	0.040	0.7	0.193	0.072	2.7
util3	0.150	0.081	1.8	0.048	0.043	1.1	0.360	0.076	4.7
util4	0.217	0.105	2.1	0.083	0.050	1.7	0.403	0.084	4.8
util5	0.180	0.115	1.6	0.030	0.046	0.7	0.391	0.079	4.9
util6	0.317	0.126	2.5	0.144	0.043	3.3	0.562	0.074	7.6
util7	0.368	0.138	2.7	0.186	0.053	3.5	0.712	0.084	8.5
line	-5.68E-5	8.48E-5	-0.7	-2.7E-5	3.8E-6	-7.2	-4.2E-5	6.1E-6	-6.8
pmt/line	-13.651	5.659	-2.4	-1.121	0.164	-6.8	-2.551	0.187	-13.7
pur/line	2.563	0.915	2.8	0.523	0.100	5.2	1.983	0.150	13.2
int_score	-0.023	0.005	-4.3	-6.1E-3	2.7E-4	-22.6	-1.7E-2	4.1E-4	-40.7
ext_score	4.67E-3	3.56E-3	1.3	-3.1E-3	1.9E-4	-16.5	-6.4E-3	2.6E-4	-24.4
unemp	-1.57E-4	1.15E-3	-0.1	1.3E-4	1.1E-3	0.1	-5.0E-3	3.9E-3	-1.3
noinsure	5.89E-4	2.55E-4	2.3	6.1E-4	2.6E-4	2.4	-6.8E-4	1.9E-3	-0.4
house	5.84E-7	7.49E-7	0.8	7.1E-7	7.5E-7	0.9	-7.8E-6	1.1E-5	-0.7
# of Obs		360840			360840			295415	
Log Lik		-11320.5			-11345.4			-36417.4	
Pseudo R2		0.1397			0.1378			0.1526	

Marginal Effects (percentage points per month)

	Interact with Age (1)				Update Credit Line (2)			
quarter	stigma	s.e.	riskcomp	s.e.	stigma	s.e.	riskcomp	s.e.
qtr1	0.000%		0.000%		0.000%		0.000%	
qtr2	0.163%	.0206%	0.000%	.0033%	0.206%	.0215%	-0.001%	.0028%
qtr3	0.201%	.0254%	0.013%	.0056%	0.251%	.0269%	-0.005%	.0043%
qtr4	0.195%	.0266%	0.015%	.0070%	0.245%	.0290%	-0.011%	.0049%
qtr5	0.228%	0332%	-0.003%	.0070%	0.298%	.0377%	-0.030%	.0052%
qtr6	0.270%	.0386%	-0.001%	.0130%	0.364%	.0445%	-0.043%	.0055%
qtr7	0.212%	.0336%	-0.004%	.0109%	0.290%	.0410%	-0.049%	.0058%
qtr8	0.210%	.0360%	-0.008%	.0079%	0.303%	.0453%	-0.053%	.0060%

Notes: See Table 2. Interaction terms in (1) are not shown.