A Portfolio View of Consumer Credit*

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Abstract

This paper takes a portfolio view of consumer credit. Default models (credit-risk scores) estimate the probability of default of individual loans in isolation (first moments). But to compute risk-adjusted returns, lenders also need to know the covariances of the returns on their loans with aggregate returns. Covariances are independently relevant for lenders who care directly about the volatility of their portfolios, perhaps because of Value-at-Risk considerations or the structure of the securitization market. Cross-sectional differences in these covariances also provide insight into the nature of the shocks hitting different types of consumers.

We use a unique panel dataset of credit bureau records to measure the "covariance risk" of individual consumers, i.e. the covariance of their default risk with aggregate default rates. We obtain two key results. First, there is significant systematic heterogeneity across consumers in covariance risk, which lenders can potentially utilize. Second, we analyze the cross-sectional distribution of credit. We find that the amount of credit (especially revolving credit) obtained by consumers significantly decreases with their covariance risk, though the effect is smaller in magnitude than that of credit scores. It appears that some lenders take covariance risk into account, at least in part, in determining the amount of credit they provide.

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A basic principle of financial economics is that risk is properly viewed in a portfolio context. That is, the relevant measure of an investment's risk (i.e. the measure relevant for discounting) is the risk that it adds to the portfolio of all investments. The traditional subject of portfolio-risk research has been equities. By contrast consumer loans have received little academic analysis, especially portfolio-level analysis, even though they are typically held in large portfolios of thousands or even millions of loans, orders of magnitude more populated than most equity portfolios. The overall consumer credit market in the US is quite large, amounting to about $7 trillion by the start of the decade (of which about $5.4 trillion is mortgage debt, $800 billion is other installment debt, and $700 billion is revolving debt) [Federal Reserve System (2001)]. Much of this debt is originated by large, national lenders. This debt is typically either held by the originator in large portfolios, or sold into large securitization pools [Gorton and Souleles (2004)].

The goal of this paper is to provide a portfolio view of consumer credit. Lenders usually gauge the risk of their consumer loans by credit-risk scores, which measure a consumer's expected probability of default in isolation (a first moment). But the aggregate volatility of a portfolio of loans also depends on the cross-sectional covariances of the default risks of its component loans (second moments). For example, the economies of some regions of the country are more cyclical than others. Suppose that default rates in Alaska have a relatively low covariance with default rates in other states; i.e., that Alaskans default relatively less when people in other states default relatively more, and vice versa. Then loans to Alaskans entail less "covariance risk" and so bring diversification benefits to a large portfolio of debt, contributing relatively little to the volatility of the portfolio.

This paper uses a unique panel dataset of credit bureau records to construct measures of covariance risk analogous to those from equity research. We analyze the underlying demographic determinants of consumers' covariance risk, and test whether consumers with lower covariance risk receive more credit, *ceteris paribus* (*c.p.*).

There are several reasons for lenders to care about covariance risk. First, the insight of Sharpe (1964) and Lintner (1965) applies to all assets, not just equities: In equilibrium, the market price of a consumer loan should depend on the risk that the loan adds to the market portfolio. If, analogously to the literature on equity investors, we take consumer lenders to be optimizing over their own asset class, in this case consumer loans, then the risk-adjusted expected return of a consumer loan would decline as its covariance with the market portfolio of all consumer loans declines.[1]

Second, there are several important institutional features of the consumer credit market that directly motivate lenders to regulate the volatility of their portfolios. Lenders typically assess the adequacy of their capital through 'Value-at-Risk' calculations, which estimate the probability that losses at the portfolio-level exceed some given threshold [Saunders (1999)]. Indeed, the new Basle II rules require that lenders set their capital levels as a function of such calculations. Also, many lenders rely on securitization to finance a large part of their loans. If total losses in a pool of securitized loans exceed a threshold, the securitization either defaults or enters early amortization, a pre-payment risk for the lender. The portfolio risk of the pool determines how the securitization must be structured to avoid such outcomes and receive desired bond ratings.[2]

[1] As discussed below, the literature on equities analogously computes covariances with just the market portfolio of stocks, often proxied by the S&P 500. While it is most natural to compute covariances with the aggregate portfolio of all consumer loans, we could compute covariances with any subportfolio of interest in our data.

[2] For instance, imagine that a lender knows, based on credit-risk scores, that the expected default rate on a pool of consumer receivables is exactly 5%. This is consistent with two very different scenarios: 1) in a state of the world

Hence the insight of Markowitz (1959) applies to the construction of portfolios of consumer loans: If a lender cares about the risk that a loan *adds* to his portfolio, he should prefer loans with low covariance risk, *c.p*.

Our methodology is analogous to that of the equity-pricing literature. Using individual consumers as our unit of observation, we track their credit scores to approximate the monthly returns experienced by their lenders. We then aggregate these individual time series into a time series of market returns, and compute each consumer's "default beta" as the covariance of his individual returns with market returns (i.e., as the slope coefficient in the regression of his individual returns on the market returns). These default betas measure consumers' covariance risk.

After computing the default betas, we investigate two key issues. First, is there systematic heterogeneity in the betas across consumers? For instance, how does covariance risk vary with income and age and with local economic conditions? The answer to this question helps characterize the shocks hitting different types of consumers, and so is of macroeconomic interest. The question is also of interest from the point of view of a lender. A lender can directly compute the beta of a current borrower because a time series of her credit usage is available in-house. But in the absence of a time series, a potential new borrower's beta must be estimated from her

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that occurs 5% of the time (e.g. a recession), everyone in the pool defaults, and 2) in all states of the world, 5% of the pool defaults. In scenario 1 the individual receivables are perfectly correlated (maximal covariance), whereas in scenario 2 they are altogether uncorrelated (zero covariance). The lender would presumably prefer scenario 2, *c.p.*. Since a constant 5% of the pool is defaulting in every given year, the aggregate cash flows from the pool are smooth relative to scenario 1. This makes it easier to securitize the pool, since a claim on say the first 95% of the pool's cash flows would pay 100 cents on the dollar no matter what. By contrast, a lender in scenario 1 has a problem. No claim on the pool is risk-free without complete credit-enhancement. Hence the receivables' covariance structure determines how the pool can be carved into different securities, and the type and amount of credit-enhancement required. The securitization market shows informal appreciation of this covariance risk, in that a new issue's prospectus will usually include some information regarding the diversification of the pool, such as its distribution across geographic and other characteristics (e.g., the age of the debts).

current characteristics. The second issue we investigate is whether empirically lenders put some weight on covariance risk in determining the amount of credit they provide. It is well known that lenders take into account a consumer's expected probability of default, in particular as measured by his credit score. The open question is whether consumers with greater covariance risk obtain less credit, even controlling for their scores and other factors. More generally, this is the first paper we know of to study the determinants of the cross-sectional distribution of credit using the comprehensive credit bureau data.

We obtain two key results. First, there is significant systematic heterogeneity across consumers in covariance risk, which lenders can potentially exploit. Covariance risk is higher for younger and single consumers, lower-income consumers, those who rent rather than own, and those from states with higher rates of divorce and lower rates of health-insurance coverage. Second, the amount of credit obtained by consumers significantly declines with their covariance risk, *c.p.*, even controlling for their credit-risk scores and other variables. We find declines in both total credit and revolving credit such as bank-card credit, in both the number of loans and in the dollar value of credit extended. It appears that some lenders do take covariance risk into account, at least in part, in determining the amount of credit they provide, especially revolving credit. Nonetheless, the effect of covariance risk on credit is much smaller in magnitude than that of the credit scores.

The rest of the paper is in five sections. Section I discusses how we extend asset pricing theory to consumer credit. Section II describes the dataset, and Section III our econometric methodology. Section IV reports the results, and Section V concludes.

I. Applying Asset-Pricing Theory to Consumer Credit

As Markowitz (1959) observes, the risk of a security that affects the risk borne by its investors is the risk that it adds to a well-diversified portfolio. Consequently, risk-averse investors should prefer securities whose payoffs covary relatively less with their current portfolios, *c.p.* Sharpe (1964) and Lintner (1965) show that, in equilibrium, investors all hold the value-weighted portfolio of all assets, so all investors should prefer lower covariance with this portfolio. Specifically, the market clears when expected returns are linear in betas.

The standard application of this covariance-pricing theory is to equities. Much of the equity market is held through well-diversified portfolios, so that it is plausible that there is greater investor demand for stocks with a low (CAPM) beta relative to the value-weighted portfolio of all equities. This theory is relatively easy to test because equity-return data are widely available. Empirical research (e.g. Fama and MacBeth (1972)) generally supports covariance-pricing: stocks with higher betas have historically paid higher subsequent returns.

Our analysis applies this covariance-pricing intuition to consumer credit, where data has been more scarce. Consumer credit is also held through well-diversified portfolios. In fact, the major components of household debt, i.e. mortgages, car loans and bank-card debt, are held almost exclusively in portfolios with thousands or even millions of loans, so by this measure there is greater diversification in the consumer credit market than in the stock market. This suggests that consumer lenders might prefer lending to consumers who bring a covariance benefit to the market portfolio of consumer loans.

The equity-market literature relates expected stock returns to betas relative to the market portfolio of equities, which is only a subset of the market portfolio of all assets. Strictly speaking, this is consistent with the underlying theory under the additional simplifying assumption that equities are held by investors who hold only equities. We can motivate our application to consumer credit analogously, by assuming that consumer loans are held by agents who hold only (or largely) consumer loans. As noted above, institutional features of the financing of consumer loans provide independent motivation for our application.

The equity-market literature focuses on the pricing of securities, taking the quantities of securities to be fixed. That is, the preference for lower beta is associated with a higher price, not higher quantity. However, if quantities are endogenous we should expect adjustment of both in equilibrium. Both are surely endogenous even in the short run in the consumer credit market, so in this case theory predicts that credit supply increases as covariance risk declines. Credit bureaus collect rich data on the quantities of credit, not the prices (interest rates), so this is the prediction on which we focus.

To apply the equity-pricing method to consumer credit we need to calculate the return that a consumer's lenders make on their loans to him during each month. Unlike stocks, consumer debt is not publicly marked to market. Even the credit bureaus do not directly record these returns, but we can proxy for them by using the reported time-variation in consumers' probability of repayment. The change in this probability approximates the price return on loans to the consumer.

Our dataset includes for each consumer monthly observations of their Fair Issacs Company (FICO) credit-risk score, which is the industry-standard measure of consumers' default risk. The credit scores summarize the information in each consumer's credit file regarding the probability of being seriously delinquent over the next two years, where 'seriously delinquent' means anything from 90+ days delinquent to bankrupt.[3] In practice lenders rely heavily on the scores in setting their credit-policy for each consumer, often using them as summary statistics for the consumer's credit-worthiness and profitability [Moore (1996)]. Thus we let $p_{i,t}$ be the default probability implied by consumer *i*'s credit score as of date *t*.

We can use these default probabilities to mark to market a stylized consumer credit. Consider a consumer who has borrowed one dollar and promised to repay it at a future date, so that the market value of the loan on date *t* is approximated by $1-p_{i,t}$, the probability of repayment. Then the return on the loan at date *t* is approximated by $p_{i,t-1} - p_{i,t}$, the change in the probability of repayment. Because it is more natural to analyze the change in *p* rather than -1 times the change in *p*, we analyze $p_{i,t} - p_{i,t-1}$. That is, we refer to changes in the probability of default -- and 'default betas' -- as opposed to changes in the probability of repayment. Because we will look at covariances between time series that have both been multiplied by -1, this normalization is of no consequence.[4]

II. Data Description

This paper uses a unique, proprietary panel dataset of credit files from one of the major U.S. credit bureaus, Experian. The dataset tracks approximately 100 thousand randomly sampled consumers monthly from 1997:03 to 2000:03, a total of 37 months.[5]

[3] Gross and Souleles (2002) verify that the scores are very significant predictors of consumer default. Musto (2004) also analyzes credit bureau scores.

[4] More generally, we only need that the *p* we use be linearly related to the probability of default. This implies that we cannot use the credit scores directly, because as noted below they are calibrated as non-linear functions of default rates.

[5] The sample is a geographically stratified random sample. The unit of observation is an individual, not a household. Our dataset includes an artificially generated ID variable that allows us to link the records of a given individual over time, without identifying the individual.

Credit bureau files contain comprehensive summaries of the credit relationships (‘trades’) established by each consumer. For each credit trade, there are various measures of the amount of debt held and the repayment performance. The underlying data are obtained primarily from the creditors, mostly financial institutions and retail lenders. Our dataset contains the partially aggregated credit reports for each consumer that are available to lenders to evaluate whether to lend to the consumer. These reports aggregate the consumer’s individual trades into categories reflecting different types of credit, such as mortgages, auto loans, credit cards, etc. For each consumer-month, the dataset includes dozens of variables summarizing credit usage and delinquency, as well as credit limits where applicable. For example, for bank-cards the available variables include “Total number of open bankcard trades,” “Total number of bankcard trades presently 90 or more days delinquent or derogatory,” and “Total (sum) of credit limit on all open bankcard trades”[6]. There are analogous variables for the other credit categories.

We merge this data with another, proprietary research dataset from Experian that contains salient individual demographic characteristics such as marital status, gender, number of children, housing status (rent vs. own), date of birth and income. This demographic information covers about 80% of the credit-file sample, though some variables are populated more than others.[7] We further augmented this individual-level data with measures of local economic conditions in the region in which each consumer lives (based on state and zipcodes), such as the county unemployment rate. These demographic and regional variables allow us to investigate the underlying determinants of covariance risk.

[6] Bank cards include Visa, Mastercard, Discover, and Optima cards, as opposed to cards from retailers.

[7] This demographic information is not part of consumers’ credit bureau files. It was obtained from a variety of public and propriety sources, including census and marketing databases. For example, homeownership is determined from tax assessor and deed information, supplemented by a model predicting homeownership as a function of consumer characteristics.

Table 1 provides summary statistics for the main variables used in the analysis below. In 2000 the average consumer in our sample had a total of 6.6 open credit relationships (*AllTrades00*). Of these trades, 1.7 were nonrevolving (*Nonrevolving00*), so the majority were revolving trades such as credit cards. The average sum of limits across all open bankcards was about $18 thousand. The large standard deviations around these averages imply substantial heterogeneity in all these measures of credit.

The resulting dataset is ideally suited for the purposes of this paper. Most notably it includes the credit-risk scores, which summarize lenders' own expectations regarding the probability of default -- the first moment p. We do not need to estimate this probability ourselves; we use the actual (transformed) probabilities that the lenders themselves use. With a long time series of scores for each consumer, we can compute for each consumer the covariance – a second moment – of the time series of changes in his probability of default with the corresponding aggregate time series. Also, we have rich measures of the credit obtained by each consumer, so we can test whether credit supply varies with the consumer's covariance risk, even controlling for his credit score.

The credit score is an ordinal measure of the likelihood of default over the next 24 months, originally calibrated from actual default rates. We invert this calibration to recover the cardinal probability units.[8] For each consumer i and month t we produce $p_{i,t}$, the expected probability of default. Then $r_{i,t} \equiv p_{i,t} - p_{i,t-1}$ is the monthly change in the probability of default. As

[8] We estimated a logit model of default over the next two years (1997:04-1999:03) as a function of the initial credit score in 1997:03, and use the resulting probabilities of default for p. Consistently with the definition of the scores, we include in default both bankruptcy and non-bankruptcy delinquency (90+ days late), conditional on not already starting in default in 1997:03. We use a cubic polynomial in the score, because the score is known to be constructed as a nonlinear function of default rates.

discussed above, with its sign reversed, $r_{i,t}$ proxies for the monthly return to lending to the consumer.

The default betas that we estimate below capture the systematic component of each consumer's default risk. The remaining component is idiosyncratic. In principle a lender can diversify away this idiosyncratic risk by holding a large, diversified portfolio of loans. To gauge the potential scope for diversification of consumer loans, we first contrast the results of holding diversified and undiversified portfolios of various sizes. Figure 1 illustrates the distribution of 'long-run returns' across various portfolios, using the 3-year change in the probability of default, $r_{i,long} = p_{i,2000:03} - p_{i,1997:03}$. The horizontal axis records the number of consumers in each portfolio, the vertical axis measures the standard deviation of returns cross-sectionally across 100 portfolios of each size. The figure is analogous to well known figures showing the effects of diversification across stocks, sometimes constraining stock portfolios to one country or industry [e.g., Solnik (1974)].

The (higher) line labeled 'random' allocates consumers randomly across the 100 portfolios. The resulting standard deviation drops quickly with portfolio size, from about 1.6% for a portfolio with only one consumer, to only .06% for a portfolio of size 600, with most of the decline coming from the first few hundred consumers. This decline suggests a large scope for diversification. Lenders do not, of course, hold equally weighted, random portfolios of consumer loans. For comparison, the line labeled 'geo' reflects the geographically worst diversified portfolio, successively adding to each portfolio the consumer with the next closest zip code in the sample.[9] The standard deviation still drops quickly with portfolio size. Nonetheless it asymptotes

[9] To construct the random portfolios, within each portfolio we randomly ranked each consumer 1-600, then formed portfolios of size 1-600 based on these ranks. We compute the mean return $r_{*,long}$ within each portfolio, and then

to only about .10%, about two-thirds larger than the asymptote of the random portfolio. This difference suggests that the costs of holding undiversified portfolios, even large portfolios, can be large. More generally, these results suggest that there might be substantial systematic heterogeneity in default risk across consumers of different characteristics, including here geographical location. It remains to be seen whether lenders take this heterogeneity into account in extending credit.

III. Econometric Methodology

We begin by estimating consumers' default betas, by computing the covariance of the time series of each consumer's monthly changes in default probability with the corresponding time series for the monthly 'aggregate' changes in default probability. Specifically, for each consumer *i*, we run the following regression:

$$r_{i,t} = \alpha_i + \beta_i r_{*t} + \varepsilon_{i,t}, \qquad (1)$$

where r_{*t} is the cross-sectional average of the change in default probabilities $r_{i,t}$ within the entire sample in month t. The resulting coefficient β_i is consumer i's 'default beta'. A larger default beta represents greater covariance risk.

Below we study how the betas affect credit supply, including the change in credit over the final year of the sample period, 1999:03-2000:03. Accordingly, to avoid endogeneity, we compute the betas in equation (1) using data from the preceding part of the original sample period, t =1997:04 through 1999:03. Reducing the beta-estimation period from 36 to 24 months increases the estimation error in our betas, making it harder to find an effect of the betas on

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compute the cross-sectional standard deviation of $r_{*,long}$ across portfolios. We repeat this exercise 10 times and graph the average results. To start each of the 100 geographically undiversified portfolios, we randomly sampled consumers subject to the constraint that the consumer have 600 unselected consumers around him (in zip-code credit.[10] Even so, we find that almost 25% of the betas are statistically significantly different, at the 5% level, from 1 (the average beta). This suggests that the informational content of the estimated betas is relatively high.

We also consider a number of robustness checks in computing the default betas. For instance, we compute analogous betas using the change in credit scores directly $(Score_t - Score_{t-1})$, as opposed to the change in the transformed probabilities of default. We also use non-overlapping, two-month changes in the default probabilities $(p_t - p_{t-2})$. The conclusions below are robust to these changes, though sometimes somewhat weaker in magnitude using the two-month changes because of the shorter effective sample period.

After computing the default betas, we investigate two issues. First, is there systematic heterogeneity in the betas? Second, do lenders take covariance risk into account in determining the amount of credit they provide?

To investigate the first issue, heterogeneity in the default betas, we estimate the following equation, cross-sectionally across consumers i:

$$\beta_i = \gamma_0 + \gamma_1 \boldsymbol{X}_i + \varepsilon_i, \tag{2}$$

where vector $\boldsymbol{X}_i$ includes the demographic characteristics of consumer i available in the dataset. These variables are flexibly specified as a series of indicator variables. To maintain sample size,

space). To each of these starting portfolios we add the consumer with the closest zip code, among the remaining consumers, to the first portfolio-member's zip code.

[10] To improve precision we limited the sample to consumers where $r_{i,t}$ is available for all 24 months. This retains about 94% of the sample. The results below are qualitatively similar, though sometimes less significant, on including the entire sample.

instead of dropping observations with missing demographic characteristics, we include additional indicator variables for the missing values with the original indicator variables then set to zero.[11]

We sometimes augment these individual-level variables with measures of local economic conditions in the region in which each consumer lives. Gross and Souleles (2002) show that such variables help predict the incidence of consumer default, even controlling for credit scores. *Unemployment* measures the county-level unemployment rate.[12] This data is available monthly. Since the betas are computed using data starting in 1997:03, we take the unemployment rate from 1997:03. This timing allows us to assess the effect of unemployment on subsequent default behavior. It is also consistent with the point of view of a lender who wishes to estimate betas for potential new customers. $\boldsymbol{X}_i$ also includes the fraction of people in the state without health insurance (*Noinsurance*) and the divorce rate in the state (*Divorce*).[13] These variables are available only annually, and so we take them from 1997. In specifications including the regional variables, the standard errors are adjusted to allow for within-state correlation.

Other specifications replace the regional variables with state dummy variables. These variables control for all state-level geographic effects on covariance risk. These effects include state regulations and other factors like state bankruptcy laws that affect the costs of default, the composition of jobs across occupations and industries in the state, as well as the correlation of

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[11] Eq. (2) does not control for the consumers' credit scores because they are likely to be simultaneously determined with the betas and hence endogenous. Eqs. (3) and (4) by contrast can use both the scores and the betas as control variables.

[12] The Department of Labor does not provide the county-level unemployment rate for some counties. For consumers living in those counties (about a quarter of the sample) we substitute the state-level unemployment rate.

[13] The divorce variable (which comes from the Department of Health and Human Services) is missing for a few states. To avoid dropping all observations in these states, we instead introduce a dummy variable for missing divorce data. The divorce rate is computed in per capita terms, since the only readily available normalizing variable is state population.

the state business cycle with the national business cycle, etc. The state dummies also control for all differences in average household characteristics across states.

The second issue we examine is whether lenders take some account of covariance risk in their lending decisions, at least on average. To test whether default betas influence the amount of credit obtained by consumers, we estimate the following cross-sectional equation:

$$Credit_{i,00} = \gamma_0 + \gamma_1 Score_{i,99} + \gamma_2 \beta_i + \gamma_3 \boldsymbol{X}_i + \varepsilon_i , \tag{3}$$

where $Credit_i$ represents various measures of the credit granted to consumer i, and $Score_i$ is i's credit-risk score. The score summarizes the expected probability of default. While lenders rely heavily on the scores in allocating credit, since they are not available in traditional household datasets used in previous studies, their importance in credit supply has not been previously systematically studied. Since larger scores imply a smaller probability of default, we expect to find larger scores associated with more credit. We will quantify how much credit increases with the score.[14]

By contrast, less is known about whether lenders also take covariance risk into account. They might put some weight on diversifying their loans across certain characteristics, but this weighting might be done informally, not quantitatively. If lenders exhibit some preference for consumers with low covariance risk, even after controlling for consumers' credit scores, the coefficient γ_2 on the default beta will be negative. On the other hand, if lenders care only about the first moment of default, then γ_2 will be insignificantly different from zero.[15]

[14] We use the scores and not the related probabilities of default because lenders themselves use the scores, not the probabilities directly. The conclusions below are robust to using cubic polynomials in the scores. Hence the default betas are not simply picking up nonlinearities in the effect of the scores. Eq. (3) introduces the scores linearly only for ease of interpretation.

[15] To minimize the role of outliers when the estimated betas are used as independent variables, in eqs. (3) and (4) below we drop betas with absolute values above 10. Such outliers represent only about 1-2% of the sample. In eq. (2), which has beta as the dependent variable, we do not drop the outliers in the reported results (which reduces the

Of course, the probabilities of default, and so the credit scores, are themselves significantly influenced by the amount of debt consumers hold. Covariance risk might also be affected by debt. To minimize endogeneity, in eq. (3) the score and the beta are lagged one year relative to the dependent variable *Credit*. Specifically, we measure *Credit* as of 2000:03 and the score as of 1999:03, while the beta was computed over 1997:04-1999:03. This timing is also consistent with the analysis below of the change in credit over the final year of the sample period, 1999:03-2000:03, which further helps avoid endogeneity.

Eq. (3) will sometimes also control for $\boldsymbol{X}_i$, specifically the individual-level demographic characteristics and state dummy variables described above. Including these variables does not imply that lenders directly condition on such demographic and regional variables in setting credit supply; the variables might simply be correlated with other factors on which lenders condition.[16] Nonetheless we sometimes include $\boldsymbol{X}_i$ in order to test whether any estimated effect of the betas on credit might simply reflect the correlation of beta with demographic and regional characteristics, not directly beta itself. If beta is significant even controlling for $\boldsymbol{X}_i$, then beta contains additional information relevant for credit allocations above and beyond the heterogeneity studied in eq. (2). Also, the cross-sectional distribution of credit across different demographic characteristics is of independent interest.

The credit bureaus characterize credit relationships by type, one of the key distinctions being revolving versus non-revolving credit. Non-revolving credit consists mostly of mortgages, auto loans, and other installment loans. Such loans typically involve borrowing a fixed amount

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adjusted R^2), but we have verified that the conclusions are not driven by outliers. Eqs. (3) and (4) do not take into account the fact that the betas were estimated in a previous stage.

[16] Indeed, under the Equal Credit Opportunity Act lenders cannot directly condition on certain demographic characteristics, including gender, age and marital status, as well as race, religion, and national origin.

against a given purchase and repaying this amount with interest over time according to a pre-arranged schedule. By contrast, revolving loans are typically open-ended and uncollateralized. The most important example is credit cards, which give the borrower a flexible line of credit. In addition to having different contractual features, revolving and non-revolving loans can differ in the type of information available to lenders that might help them assess the covariance risk of different consumers. For both types of loans lenders obtain salient information at the time of application, but the application information is typically richer for non-revolving loans. On the other hand credit card issuers continue to manage the credit card limit over time. In doing so they can take advantage of the rich information that they accumulate over time concerning the past behavior of their customers.

Accordingly, to allow for potential differences in the ability and practice of different lenders to assess and put weight on consumers' covariance risk, in eq. (3) we use different measures of $Credit_{00}$. We distinguish revolving and non-revolving credit by examining both the total number of credit trades for each consumer, and separately the number of non-revolving trades. The difference between these variables is of course the number of revolving trades, which are largely credit cards. We also consider the intensive margin of revolving credit by studying total credit card (bankcard) limits for each consumer. Compared to non-revolving debt, with revolving debt one can more readily distinguish credit supply from credit demand by focusing on credit limits as opposed to credit balances.[17]

Even though the credit score and default beta used in eq. (3) are lagged, and so contain only information available by 1999:03, some of the credit relationships recorded in the dependent

[17] Gross and Souleles (2002a) use this distinction to study the effect of high frequency, exogenous changes in credit supply.

variable might have been initiated before 1999:03. To minimize any resulting endogeneity, we also estimate the relation between credit and beta in differences:

$$d(Credit)_{i,00} = \gamma_0 + \gamma_1\, Credit_{i,99} + \gamma_2\, d(Score)_{i,99} + \gamma_3\, \beta_i + \gamma_4\, \beta_{i*}\, d(Score)_{i,99} + \gamma_5\, \boldsymbol{X}_i + \varepsilon_i\,, \quad (4)$$

where $d(Credit)_{00}$ is the change in credit between 2000:03 and 1999:03. Working in differences also controls for all individual fixed effects in the level of credit. Further, to allow the magnitude of the change in credit to vary with the initial amount of credit, $Credit_{99}$ is the starting amount of credit in 1999:03. To allow a discontinuity for people starting without any credit, we also include an indicator (*Credit99_zero*) that equals one if the number of trades in 1999:03 is zero.

What could prompt lenders to supply more credit to a given consumer? One of the most important factors would be an increase in her credit score. Accordingly the independent variables include the change in the score. To avoid endogeneity the change is lagged, and computed over the same two-year period over which the beta is computed: $d(Score)_{i,99} = Score_{99:03} - Score_{97:03}$. This timing treats the beta and the score symmetrically. It is also consistent with the point of view of a lender who, in considering in 1999 whether to extend credit to consumer i, considers all variables potentially available at the time.

For a given change in the credit score, the resulting change in credit might vary with the consumer's default beta. Hence eq. (4) also adds the interaction of beta with the change in score, $\beta_{i*}\, d(Score)_{i,99}$, as well as the beta directly. We expect the coefficient γ_4 on the interaction term to be negative (or non-positive), implying that a consumer with a larger default beta receives a smaller increase in credit for the same increase in his score. Such a result would be especially suggestive that lenders give some consideration to covariance risk in allocating credit. Some specifications will also control for the individual-level demographic characteristics and state dummies in $\boldsymbol{X}_i$.

IV. Results

We begin by analyzing the estimated default betas. Is there systematic heterogeneity in the betas across consumers that lenders can potentially take into account in supplying credit? We next proceed to analyze the actual supply of credit. Do consumers with greater covariance risk obtain less credit, even controlling for their expected probability of default and other factors?

Table 2 presents tests for heterogeneity in the estimated default betas, following eq. (2). As a starting point, Column (1) considers only individual-level demographic characteristics. The omitted demographic categories are low income (below $25 thousand), young (below age 30), unmarried, female, one child, one adult, renter, and not a business owner. The indicator variables for missing or unknown demographic values are labeled with the suffix 'Mis'.[18] The demographic variables are jointly statistically significant, and many are individually significant. Starting at the top of the column, the default betas significantly decline with income. The beta of a high-income consumer (above $50 thousand) is about 0.17 smaller than that of a low-income consumer, *c.p.*. Relative to the average beta of 1.0, this effect is also economically significant. Further, the betas decline monotonically with age, with the effect large in magnitude. Consumers aged 60 and above have average betas about .33-.47 smaller than those of young consumers. Hence high income and older consumers exhibit less covariance risk – they are less likely to default when the aggregate default rate is high, and vice versa, relative to other consumers. The betas are also smaller for consumers that are married, female, have children, or own their homes.

[18] For missing values the corresponding original indicator variables are set to zero, so the coefficients on the 'Mis' indicators should be interpreted relative to the omitted categories. (The indicator 'DemographicsMis' refers to consumers for whom no individual-level demographic variables are available at all. The other 'missing' indicators identify missing demographic values for the remaining consumers for whom some demographic variables are usually available.) The variable for number of kids is taken from birth records and other sources that help identify the

Column (2) instead considers local (state and county) economic conditions in the region in which the consumer lives. These conditions are measured as of 1997, in order to see their effect on the default betas which were estimated over 1997-1999. The regional variables are jointly significant. The betas significantly increase with the fraction of people in the state lacking health insurance and the divorce rate in the state. The coefficient on unemployment is also positive, though insignificant.[19] Hence, in addition to increasing the probability of default, as previously studied, adverse regional shocks also tend to increase covariance risk. Column (3) includes both the individual and regional characteristics. The results are qualitatively similar to those in the previous columns, though the divorce rate is no longer significant given the individual controls.

Column (4) replaces the regional controls with state dummy variables, which control for all state-level geographic effects on covariance risk. The (unconditional) sample average default betas vary substantially across states, ranging from about .7 on average in New Hampshire and Alaska to about 1.5 in Delaware. Generally the betas tend to be larger in the South and smaller in New England. In Column (4) of Table 2 the state dummies (not shown) are jointly statistically significant. That is, even controlling for the available individual-level characteristics, the betas still vary significantly across states. Nevertheless the individual characteristics remain significant.

It is noteworthy that the effects of these demographic and regional characteristics on the default beta tend to have the same sign as their effects on the probability of default. That is, consumers that are risky in terms of their default probability (the first moment *p*) also tend to

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number of children when children are present, but do not directly identify households with no children. Hence 'KidsMis' reflects both missing/uncertain values and zero children.

have greater covariance risk (the second moment β).[20] This could reflect the possibility that consumers that are on the edge of default (with large *p*) are very vulnerable to aggregate shocks, whereas those far from default might face more idiosyncratic shocks.

In all four columns the adjusted R^2 is small, indicating that these individual and regional characteristics explain only a small fraction of the cross-sectional variation in the estimated betas. Presumably this partly reflects measurement error in the individual demographics and imprecision in the estimated betas.[21] Nonetheless the individual and regional variables are jointly quite significant. We conclude that there is significant systematic heterogeneity across consumers in their default betas.

Table 3 tests whether the differences in consumers' default betas affect the amount of credit they actually receive. The three pairs of columns consider the total number of credit trades, the number of non-revolving trades, and total credit card limits for each consumer, respectively. Following eq. (3), to minimize endogeneity credit is measured as of 2000 (*Credit00*) whereas the credit score is taken from 1999 and the beta is computed over 1997-1999. Table 3 begins with the total number of trades, $AllTrades_{00}$. Column (1) includes as independent variables only the credit score and beta. The score has a large, positive effect on the number of trades. This effect is hugely significant, with a t-ratio above 100. Cross-sectionally, increasing the score by one standard deviation (about 0.9) increases the number of trades by about 2. Since the average number of trades is about 7, this effect is also economically quite significant. As expected, credit

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[19] Our sample period ends before the 2001 recession, so there might not be enough variation in unemployment in the sample.

[20] The main exception is business owners, who have greater probabilities of default (lower credit scores *c.p.*), but lower covariance risk. They might face large shocks to their businesses, but these shocks might be more idiosyncratic than the shocks to other consumers.

scores play an important role in the allocation of credit. The coefficient on the default beta is also significant, with a negative sign. Consumers with greater covariance risk obtain less credit, even controlling for their expected probability of default. Cross-sectionally, a one standard deviation increase in beta (about 2.9) reduces the total number of trades by about 0.1. While this effect is much smaller than that due to the score, it is nonetheless statistically significant.

Column (2) adds the individual-level demographic characteristics and state dummies (not shown). The individual and state variables are each jointly significant. The number of trades increases with income, and exhibits an inverted-U shape life-cycle profile in age, peaking in the 50s. These effects are large in magnitude, with high income and middle aged (50-59) consumers having almost 1.5 more trades on average than low income and young consumers. The number of trades is also larger for consumers that are married and that have larger households. Homeowners and business-owners also hold significantly more trades.

Adding the individual controls and state dummies increases the adjusted R^2 substantially, from about .14 to .19, though they have little effect on the coefficients for the score and beta. However, as already explained, these results do not imply that lenders directly condition on these demographic and regional variables. Moreover the variables can of course also capture differences in the demand for credit across different consumers, not just the supply of credit. Nonetheless, even controlling for these individual and state variables the coefficient on beta remains significant and negative.

Columns (3) and (4) show analogous results for non-revolving trades (e.g., mortgages and auto and other installment loans). The pattern of coefficients is qualitatively similar to that for all

[21] As noted above, unlike Tables 3 and 4 where beta appears as an independent variable, here we do not drop outliers in the betas. The results in Tables 3 and 4 imply that the unexplained variation in beta cannot reflect only measurement error.

trades, except that the effect of age peaks earlier, in the 40s. Beta again has a significant negative effect. The smaller coefficients relative to the prior columns for total trades reflect in part the smaller average number of non-revolving trades, but also suggest that the betas matter more for revolving credit.

Columns (5) and (6) instead consider total credit card limits, the intensive margin of revolving credit. In column (5) the credit score has a significant and large, positive effect on credit. Cross-sectionally, increasing the score by one standard deviation increases average credit limits by about $14 thousand. The default beta again has a significant negative effect. A one standard deviation increase in beta reduces credit limits by about $750, a significant amount. Consumers with greater covariance risk do obtain smaller credit limits on average (the intensive margin), in addition to a smaller number of revolving credit relationships (the extensive margin). Thus the effect of covariance risk is larger in magnitude for revolving credit than for non-revolving credit (and the R^2's are also larger). This could reflect the fact that providers of revolving credit have available a richer prior performance history for their borrowers, compared to providers of non-revolving credit.

Column (6) adds the individual characteristics and state dummies, which again are each jointly significant. The pattern of signs on the coefficients is qualitatively similar to that in Column (2). The demographic effects are often large in magnitude. The credit limits of high income and middle aged consumers are $8-12 thousand larger on average than those of low income and young consumers. Homeowners and business owners also have relatively large credit limits.

Table 4 instead investigates the relation between credit and beta in differences, following eq. (4). In Columns (1) and (2) the dependent variable is the change between 1999-2000 in the number of total trades, *d(All Trades)*$_{00}$. Working in differences controls for all individual fixed effects in the level of credit. It is also consistent with the point of view of a lender who is considering in 1999 whether to extend new credit to a consumer. To control for factors motivating the change in credit, we control for the change in the consumer's credit score over the previous period (*d(CreditScore)99*), and focus on the interaction of beta with the change in score (*d(Score)99*Beta99*). For a given increase in the score, we test whether the resulting increase in credit is smaller for consumers with a larger default beta.

The dependent variables include the lagged, starting number of trades in 1999 (*Credit99*), as well as an indicator (*Credit99_zero*) that equals one if the number of trades in 1999 starts at zero. In Column (1), the lagged number of trades has a significant negative coefficient. Thus the increase in credit is smaller for consumers starting with a greater amount of credit, suggesting some mean reversion in the amount of credit across consumers. On the other hand, the indicator for zero credit also has a significant negative coefficient, implying a discontinuity at zero: consumers starting with no credit receive relatively less credit going forward.

The coefficient on the change in the credit score is significantly positive, with a t-ratio of about 40. For a consumer with a beta of zero, if her score increases by .9 (the cross-sectional standard deviation), over the next year her number of trades increases on average by about .57. Even when estimated in differences using only within-consumer variation, the score continues to have a substantial effect on the amount of credit, even within a short period of 12 months. The coefficient on the default beta is significantly negative, implying that consumers with higher covariance risk experience smaller increases in credit over time. Notably, the interaction of beta with the change in score has a significant negative effect. For a given increase in the score, consumers with higher covariance risk do in fact receive a smaller increase in credit. Consider a second consumer with a beta one standard deviation greater than zero. If his score likewise increases by .9, over the next year his number of trades will increase on average by only about .50 (≈.57 – 3.0(.009)), about 12% less than for the consumer with zero beta, a substantial amount. The R^2 from the few covariates included in Column (1) is already high at .31.

Column (2) adds the individual demographic characteristics and state dummies, which are each jointly significant. The change in the number of trades between 1999 and 2000 is greater for higher income consumers, but smaller for older consumers. The change is also larger for consumers who are male and own homes, and who live in larger households. Even controlling for the individual and state variables, the coefficients on both beta and the interaction of beta with the change in score remain significant and negative.

In Columns (3) and (4), for non-revolving trades, the change in score still has a significant positive effect. But the effect of beta is now statistically insignificant. While the interaction term is still negative, it is insignificant. (The pattern of the other coefficients is qualitatively similar to Columns (1) and (2).)

By contrast, in Column (5), for total credit card limits, beta and the interaction term have significant negative effects. For a consumer with zero beta, if her score increases by one standard deviation, over the next year her credit limits increase on average by about $1500, a large amount. For a consumer with a one standard deviation larger beta, the resulting increase in limits is about $900 smaller in magnitude, a substantial difference. Again consumers with greater covariance risk obtain less credit, especially along the intensive margin of revolving credit.

Column (6) adds the individual characteristics and state dummies, which again are each jointly significant. The pattern of coefficients is generally qualitatively similar to that in Column (2). The main exception is that the effect of age is positive. The demographic effects are often large in magnitude. Between 1999-2000, the credit limits of high income and older consumers increased by about $200 more than did the limits of low income and young consumers.

V. Conclusion

This paper takes a portfolio view of consumer credit. It uses a unique credit bureau dataset to estimate the covariance risk of individual consumers, and to analyze its underlying determinants, as well as the determinants of the cross-sectional distribution of credit.

We obtain two key results. First, there is significant systematic heterogeneity across consumers in covariance risk. Covariance risk is higher for younger and single consumers, lower-income consumers, those who rent rather than own, and those from states with higher rates of divorce and lower rates of health-insurance coverage. Second, the amount of credit obtained by consumers significantly decreases with their covariance risk, especially for revolving credit. This conclusion holds both in levels (in the cross-section) and in differences (for given consumers over time). It appears that some lenders assess borrowers' covariance risk, at least implicitly, and put some weight on it in determining the amount of credit to provide. Nonetheless the effect of covariance risk on credit is much smaller in magnitude than that of the credit scores, suggesting the possibility that lenders (especially non-revolving lenders) might benefit from more systematic and quantitative consideration of covariance risk.

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Figure 1: Diversified vs Undiversified Credit Portfolios

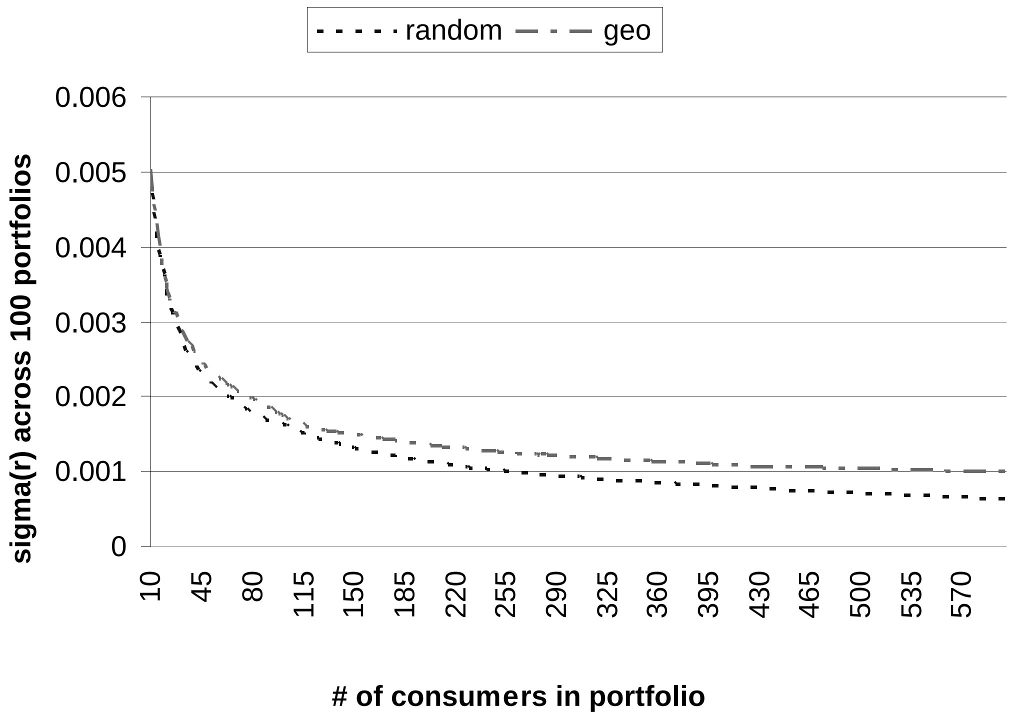

Table 1: Summary Statistics

	Mean	S.D.
AllTrades00	6.66	5.32
Nonrevolving00	1.77	1.80
CardLimits00	18.73	32.96
Creditscore99	6.45	0.92
Beta99	1.00	2.97
Income25-50	0.55	0.50
Income50+	0.30	0.46
IncomeMis	0.01	0.09
Age30_39	0.19	0.39
Age40_49	0.19	0.39
Age50_59	0.13	0.34
Age60_69	0.06	0.24
Age70+	0.04	0.21
AgeMis	0.10	0.30
Married	0.31	0.46
MarriedMis	0.13	0.34
SexMale	0.50	0.50
SexMis	0.25	0.43
Kids2	0.05	0.22
Kids3+	0.03	0.16
KidsMis	0.61	0.49
Adults2	0.24	0.43
Adults3+	0.35	0.48
Homeown	0.40	0.49
HomeownMaybe	0.16	0.37
HomeownMis	0.21	0.41
Busown	0.01	0.11
DemographicsMis	0.20	0.40
Unemployment	5.49	2.46
Noinsure	16.74	4.49
Divorce	0.40	0.19
DivorceMis	0.12	0.33

Notes

-The sample corresponds to that in Table 2. (N = 87,013, but sample size may vary with missing values.)
-The omitted demographic categories are low income (below $25 thousand), young (below 30), unmarried, female, one child, one adult, renter, and not a business owner.
-'DemographicsMis' indicates no demographic variables are available. Additional missing or unknown demographic values are labeled with the suffix 'Mis'. 'KidsMis' reflects both missing values and 0 children. HomeownMaybe is predicted homeownership. If missing, the county-level unemployment rate uses the state-level unemployment rate. State divorce rate is in per capita terms.
-Creditscore is the FICO score/100. Credit limits are in $1000s.

Table 2: Heterogeneity in the Default Beta

Default Beta	(1) Individual demographics			(2) Regional Demographics			(3) Individual and Regional Demographics			(4) Individual Demographics w/ State Dummies		
	coef	s.e.	p-val	coef	s.e.	p-val	coef	s.e.	p-val	coef	s.e.	p-val
Income25-50	-0.052	0.030	0.084				-0.057	0.031	0.075	-0.046	0.031	0.133
Income50+	-0.168	0.033	0.000				-0.161	0.037	0.000	-0.175	0.034	0.000
IncomeMis	-0.220	0.114	0.053				-0.071	0.145	0.625	-0.138	0.116	0.235
Age30_39	-0.069	0.043	0.106				-0.072	0.044	0.106	-0.071	0.043	0.100
Age40_49	-0.089	0.043	0.038				-0.087	0.040	0.034	-0.092	0.043	0.032
Age50_59	-0.102	0.046	0.027				-0.100	0.045	0.032	-0.102	0.046	0.028
Age60_69	-0.326	0.055	0.000				-0.338	0.044	0.000	-0.332	0.055	0.000
Age70+	-0.468	0.060	0.000				-0.466	0.065	0.000	-0.475	0.060	0.000
AgeMis	-0.123	0.049	0.011				-0.123	0.049	0.014	-0.134	0.049	0.006
Married	-0.107	0.033	0.001				-0.102	0.033	0.003	-0.096	0.033	0.004
MarriedMis	-0.012	0.041	0.759				-0.013	0.034	0.699	-0.014	0.041	0.730
SexMale	0.059	0.027	0.028				0.062	0.031	0.050	0.059	0.027	0.027
SexMis	0.020	0.034	0.550				0.025	0.040	0.539	0.020	0.034	0.551
Kids2	-0.124	0.055	0.024				-0.117	0.047	0.017	-0.117	0.055	0.033
Kids3+	-0.042	0.069	0.543				-0.032	0.091	0.724	-0.037	0.069	0.596
KidsMis	-0.031	0.035	0.369				-0.034	0.037	0.358	-0.030	0.035	0.393
Adults2	0.010	0.037	0.784				0.000	0.037	0.994	0.002	0.038	0.965
Adults3+	0.027	0.039	0.496				0.018	0.033	0.587	0.013	0.039	0.743
Homeown	-0.118	0.071	0.097				-0.128	0.080	0.117	-0.106	0.071	0.137
HomeownMaybe	-0.022	0.073	0.761				-0.029	0.087	0.739	-0.006	0.073	0.930
HomeownMis	0.043	0.072	0.554				0.026	0.088	0.765	0.052	0.072	0.474
Busown	-0.031	0.096	0.748				-0.045	0.111	0.684	-0.043	0.096	0.657
DemographicsMis	-0.083	0.088	0.346				-0.093	0.092	0.321	-0.085	0.088	0.334
Unemployment				0.005	0.005	0.303	0.002	0.004	0.672			
Noinsure				0.014	0.003	0.000	0.013	0.003	0.000			
Divorce				0.274	0.097	0.007	0.194	0.121	0.116			
DivorceMis				0.162	0.054	0.004	0.127	0.067	0.065			
cons	1.247	0.089	0.000	0.609	0.089	0.000	0.943	0.133	0.000	1.407	0.109	0.000
Adj. R-squared		0.0027			0.0007			0.0037			0.0038	
Obs.		87,013			85,961			85,961			87,013	

Notes: See eq. (2). The dependent variable, the Default Beta, is computed over 1997:03-1999:03. Regional demographics are taken from 1997 (3/1997 for unemployment).
-See Table 1 for description of the independent variables. Cols (2) and (3), with regional demographics, adjust the standard errors for within-state correlation.

Table 3: The Amount of Credit and the Default Beta -- Levels

Credit00	All Trades00 (1)			All Trades00 (2) w/ demographic controls			Nonrevolving Trades00 (3)			Nonrevolving Trades00 (4) w/ demographic controls		
	coef	s.e.	p-val	coef	s.e.	p-val	coef	s.e.	p-val	coef	s.e.	p-val
Creditscore99	2.134	0.019	0.000	1.895	0.019	0.000	0.164	0.007	0.000	0.120	0.007	0.000
Beta99	-0.035	0.006	0.000	-0.034	0.006	0.000	-0.005	0.002	0.000	-0.005	0.002	0.044
Income25-50				0.546	0.050	0.000				0.132	0.018	0.000
Income50+				1.356	0.056	0.000				0.352	0.020	0.000
IncomeMis				0.859	0.189	0.000				0.073	0.068	0.286
Age30_39				0.465	0.070	0.000				0.072	0.025	0.004
Age40_49				1.033	0.070	0.000				0.074	0.025	0.004
Age50_59				1.326	0.075	0.000				-0.010	0.027	0.718
Age60_69				0.393	0.090	0.000				-0.438	0.032	0.000
Age70+				-1.006	0.098	0.000				-0.868	0.036	0.000
AgeMis				0.702	0.079	0.000				0.154	0.029	0.000
Married				0.249	0.054	0.000				0.094	0.020	0.000
MarriedMis				-0.077	0.066	0.246				-0.065	0.024	0.007
SexMale				-0.417	0.044	0.000				0.242	0.016	0.000
SexMis				0.004	0.055	0.941				-0.049	0.020	0.015
Kids2				0.343	0.089	0.000				0.062	0.032	0.054
Kids3+				0.256	0.113	0.023				-0.031	0.041	0.450
KidsMis				-0.193	0.056	0.001				-0.072	0.020	0.000
Adults2				0.112	0.061	0.066				0.066	0.022	0.003
Adults3+				0.207	0.064	0.001				0.072	0.023	0.002
Homeown				1.456	0.115	0.000				0.917	0.042	0.000
HomeownMaybe				0.320	0.119	0.007				0.393	0.043	0.000
HomeownMis				0.048	0.117	0.682				0.322	0.043	0.000
Busown				1.098	0.156	0.000				0.306	0.056	0.000
DemographicsMis				0.367	0.143	0.010				0.321	0.052	0.000
cons	-7.073	0.122	0.000				0.713	0.044	0.000			
Adj. R-squared		0.137			0.191			0.007			0.073	
Obs.		85,946			85,946			85,946			85,946	

Notes: See eq. (3). The dependent variable, Credit00, is from 2000:03. The Credit score is from 1999:03, and Beta is computed over 1997:03 - 1999:03.
-Demographic controls include state dummies.

Table 3: The Amount of Credit and the Default Beta -- Levels (ctd)

	Credit Card Limits00					
	(5)			(6) w/ demographic controls		
	coef	s.e.	p-val	coef	s.e.	p-val
Creditscore99	14.278	0.114	0.000	12.512	0.117	0.000
Beta99	-0.257	0.039	0.000	-0.249	0.038	0.000
Income25-50				1.993	0.305	0.000
Income50+				8.143	0.344	0.000
IncomeMis				1.508	1.160	0.194
Age30_39				2.401	0.428	0.000
Age40_49				7.520	0.431	0.000
Age50_59				12.487	0.463	0.000
Age60_69				9.245	0.551	0.000
Age70+				2.876	0.605	0.000
AgeMis				6.487	0.487	0.000
Married				1.466	0.333	0.000
MarriedMis				-0.234	0.406	0.564
SexMale				2.884	0.268	0.000
SexMis				0.899	0.340	0.008
Kids2				0.885	0.547	0.106
Kids3+				1.663	0.693	0.016
KidsMis				-0.793	0.347	0.022
Adults2				-0.117	0.375	0.755
Adults3+				0.914	0.391	0.019
Homeown				4.705	0.708	0.000
HomeownMaybe				1.897	0.729	0.009
HomeownMis				0.190	0.722	0.792
Busown				7.151	0.957	0.000
DemographicsMis				5.487	0.879	0.000
cons	-73.076	0.746	0.000			
Adj. R-squared		0.160			0.202	
Obs.		85,946			85,946	

Table 4: The Amount of Credit and the Default Beta -- Changes

dCredit00	d(All Trades)00						d(Nonrevolving Trades)00					
	(1)			(2) w/ demographic controls			(3)			(4) w/ demographic controls		
	coef	s.e.	p-val	coef	s.e.	p-val	coef	s.e.	p-val	coef	s.e.	p-val
Credit99	-0.252	0.001	0.000	-0.257	0.001	0.000	-0.278	0.003	0.000	-0.290	0.003	0.000
Credit99_zero	-0.285	0.038	0.000	-0.222	0.038	0.000	-0.078	0.012	0.000	-0.040	0.012	0.001
d(Creditscore)99	0.626	0.016	0.000	0.626	0.016	0.000	0.118	0.008	0.000	0.112	0.008	0.000
Beta99	-0.008	0.003	0.009	-0.007	0.003	0.029	0.000	0.002	0.906	0.000	0.002	0.885
d(Score)99*Beta99	-0.019	0.005	0.000	-0.017	0.005	0.000	-0.002	0.002	0.443	-0.001	0.002	0.643
Income25-50				0.151	0.026	0.000				0.050	0.012	0.000
Income50+				0.185	0.029	0.000				0.123	0.014	0.000
IncomeMis				0.106	0.097	0.274				-0.036	0.047	0.445
Age30_39				-0.086	0.036	0.017				-0.055	0.017	0.001
Age40_49				-0.030	0.036	0.410				-0.061	0.017	0.000
Age50_59				-0.022	0.039	0.570				-0.105	0.019	0.000
Age60_69				-0.203	0.046	0.000				-0.257	0.022	0.000
Age70+				-0.571	0.050	0.000				-0.378	0.024	0.000
AgeMis				0.027	0.041	0.513				0.003	0.020	0.893
Married				0.010	0.028	0.706				0.020	0.013	0.134
MarriedMis				-0.095	0.034	0.005				-0.035	0.016	0.034
SexMale				0.218	0.022	0.000				0.072	0.011	0.000
SexMis				0.119	0.028	0.000				0.008	0.014	0.565
Kids2				0.058	0.046	0.208				-0.004	0.022	0.856
Kids3+				0.001	0.058	0.989				0.000	0.028	0.992
KidsMis				-0.002	0.029	0.946				-0.034	0.014	0.016
Adults2				0.094	0.031	0.003				0.028	0.015	0.062
Adults3+				0.110	0.033	0.001				0.026	0.016	0.098
Homeown				0.185	0.059	0.002				0.250	0.029	0.000
HomeownMaybe				0.097	0.061	0.112				0.124	0.029	0.000
HomeownMis				0.075	0.060	0.212				0.096	0.029	0.001
Busown				0.111	0.080	0.166				0.113	0.039	0.004
DemographicsMis				-0.176	0.073	0.017				-0.003	0.036	0.933
cons	0.672	0.015	0.000				0.416	0.008	0.000			
Adj. R-squared		0.305			0.315			0.152			0.164	
Obs.		85,748			85,748			85,748			85,748	

Notes: See eq. (4).
-The dependent variable, dCredit00, measures the change in credit over 1999:03-2000:03.
The initial Credit99 is from 1999:03, and Credit99_zero indicates no credit in 1999:03.
The Creditscore is from 1999:03, and the Default Beta is computed over 1997:03 - 1999:03.
-Demographic controls include state dummies.

Table 4: The Amount of Credit and the Default Beta -- Changes (ctd)

	d(Credit Card Limits)00					
	(5)			(6) **w/ demographic controls**		
	coef	s.e.	p-val	coef	s.e.	p-val
Credit99	-0.092	0.002	0.000	-0.102	0.002	0.000
Credit99_zero	-3.546	0.141	0.000	-2.958	0.143	0.000
d(Creditscore)99	1.643	0.106	0.000	1.643	0.105	0.000
Beta99	-0.191	0.021	0.000	-0.180	0.021	0.000
d(Score)99*Beta99	-0.128	0.031	0.000	-0.116	0.031	0.000
Income25-50				0.756	0.171	0.000
Income50+				1.974	0.193	0.000
IncomeMis				0.821	0.649	0.206
Age30_39				0.463	0.240	0.053
Age40_49				1.228	0.241	0.000
Age50_59				1.850	0.260	0.000
Age60_69				1.976	0.307	0.000
Age70+				0.621	0.336	0.064
AgeMis				1.399	0.272	0.000
Married				0.266	0.186	0.153
MarriedMis				-0.395	0.227	0.082
SexMale				0.644	0.150	0.000
SexMis				0.311	0.190	0.103
Kids2				0.787	0.306	0.010
Kids3+				0.917	0.387	0.018
KidsMis				-0.203	0.194	0.296
Adults2				0.213	0.210	0.309
Adults3+				0.339	0.218	0.120
Homeown				1.222	0.396	0.002
HomeownMaybe				0.786	0.408	0.054
HomeownMis				-0.353	0.404	0.382
Busown				-0.429	0.535	0.423
DemographicsMis				0.432	0.492	0.380
cons	4.400	0.080	0.000			
Adj. R-squared		0.031			0.039	
Obs.		85,748			85,748	