Risk-Based Pricing of Interest Rates in Consumer Loan Markets

by

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June 30, 2003

Abstract

This paper examines the extent and consequences of the increased use of risk-based pricing of interest rates in consumer loan markets during the mid-1990s. It tests three predictions based on these changes. First, the premium paid per unit of risk should increase. Second, debt levels should react accordingly. Third, fewer very high-risk households should be denied credit, further contributing to an increase in the spread between the interest rates paid by the highest and lowest risk borrowers.

On the whole, the results are in keeping with the predictions. For those obtaining loans, the premium paid per unit of risk became significantly larger over this time period, with the difference between high- and low-risk borrowers' interest rates approximately doubling for secured loans and increasing for most unsecured loans, as well. Given a 0.01 increase in the probability of declaring bankruptcy, the corresponding interest rate increase more than doubles for first mortgages and automobile loans and went up nearly five times for second mortgages.

In addition, changes in borrowing levels and access to debt reflected these new pricing practices, particularly for secured debt. While borrowing generally increased in the late 1990s, in part reflecting the overall lower levels of interest rates, it increased most for low-risk households who were least affected by these changes. For example, risk-based pricing may explain nearly 25% of increases in first mortgage levels. Furthermore, while these changes in pricing practices led to increased credit access for very high-risk households (again, particularly for secured debt), the increase in the risk premium faced by these households implied that their average borrowing levels either rose less or, for some loan types, fell.

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I would like to thank my advisors, Pierre-André Chiappori, Lars Hansen, Erik Hurst and Annette Vissing-Jorgensen, for their direction and advice. I also would like to thank the University of Chicago, the National Science Foundation and the Social Science Research Council for their financial support. Of course, all errors are my own.

I. Introduction

This paper examines the extent and consequences of the increased use of risk-based pricing of interest rates in consumer loan markets during the mid-1990s. Put briefly, risk-based pricing is the practice of lenders charging each borrower a specific interest rate based on credit risk rather than charging one single house rate. The paper tests three predictions based on these changes. First, the premium paid per unit of risk should increase. Second, debt levels should react accordingly. Third, fewer very high-risk households should be denied credit, further contributing to an increase in the spread between the interest rates paid by highest and lowest risk borrowers.

On the whole, the results are in keeping with the predictions. For those obtaining loans, the premium paid per unit of risk became significantly larger over this time period, with the difference between high- and low-risk borrowers' interest rates at least doubling for secured loans and increasing for most unsecured loans, as well. For example, for first mortgages, the interest rate change for a 0.01 increase in the probability of declaring bankruptcy goes from 0.16 percentage points pre-1995 to 0.38 post-1995. Figure 1 shows the increasing steepness of the interest rate schedules for nearly all the consumer loans considered.

In addition, changes in borrowing levels and access to debt reflected these new pricing practices, particularly for secured debt. While borrowing generally increased in the late 1990s, in part reflecting the overall lower levels of interest rates, it increased most for low-risk households who were least affected by these changes. For example, risk-based pricing may explain about 25% of increases in first mortgage levels. Furthermore, while these changes in pricing practices led to increased credit access for very high-risk households (again, particularly for secured debt), the increase in the risk premium faced by these households implied that their average borrowing levels either rose less or, for some loan types, fell.

The credit industry literature suggests that by the early 1980s conventional lenders were using credit scores and the like to automate underwriting standards, but as late as the early 1990s they simply posted one "house rate" for each loan type and rejected high-risk borrowers (Johnson, (1992)). As data storage costs fell and underwriting technology improved, lenders used estimates of default risk to assess different interest rates for individual loans. Indeed, Table 9 shows that variance in consumer loan interest rates increased over this period. Note that while the credit industry points to 1995 as a turning point in the use of risk-based pricing, the changes certainly occurred throughout the mid-1990s.

In order to isolate the potential effects of risk-based pricing, I empirically model interest rate determination where default risk plays a key role. I estimate the actual extent of default risk's role in interest rate setting by using two sources of risk: the risk of being late on payments and the risk of bankruptcy. Because there is only interest rate data for those who have loans, I account for selection bias using the households' reported attitudes towards debt to identify the model.

The empirical work includes a broad spectrum of consumer loans – first and second mortgages, automobile loans, credit card loans, general consumer loans and education loans – using data from the Survey of Consumer Finances (SCF) from 1983 to 1998 and the Panel Study of Income Dynamics (PSID) from 1984 to 1996. To account for the first form of default risk, I include predictions of probabilities of being delinquent on payments. Bankruptcy risk is estimated in the PSID – as the SCF before 1998 contains no bankruptcy data – and then imputed in SCF households. Standard errors are corrected using Murphy and Topel (1985).

Figure 1 shows predicted interest rates plotted against bankruptcy risk for loans with pre- and post-1995 origination dates. The critical result in these graphs is that in all cases, except general consumer loans, the slopes become steeper over time. The implication is that the differences in interest rates paid by low- and high-risk borrowers increased during this period. For example, given a 0.01 increase in bankruptcy risk, the commensurate interest rate increase more than doubled for first mortgages and automobile loans and went up nearly five times for second mortgages. For education and credit card loans, interest rate increases per a 0.01 increase in bankruptcy risk went from insignificant to 0.30 and 0.48 percentage points, respectively. A simple way to summarize this point is by looking at the default risk-premium spread – the difference in the average interest rates paid by the riskiest 20% and least risky 20% of households in the data set. By this measure, spreads approximately doubled for all secured loans and increased for credit card and education loans as well. All increases are statistically significant expect for education loans.

I also present evidence that variations over time in households' level of debt are consistent with this change in pricing practices. As the relative default risk premium falls for low-risk borrowers and increases for high-risk borrowers, we would expect that debt levels should increase more (or decrease less) for low-risk borrowers than high-risk borrowers. Furthermore, we would expect to see that very high-risk borrowers are able to get credit (albeit at high interest rates), instead of simply being denied.

Indeed, these hypotheses are generally borne out in the empirical work, and first mortgages fit the theory particularly well. As shown in Figure 2, the very high-risk households have a higher probability of holding a first mortgage post-1995 than pre-1995. Additionally, low-risk households are predicted to borrow more post-1995, consistent with a reaction to relatively lower interest rates. As riskiness increases, this effect diminishes, and households' borrowing increases less.

How much of the total changes in debt market can I explain? Changes in interest rate pricing may account for between 25% and 75% of increases in consumer debt levels for certain types of secured loans. And, these changes may more than account for the increased use of secured consumer debt by the highest risk groups.

I estimate the role of default risk in a theoretical model of interest rate determination to judge how reasonable the empirical results are. While spreads from the theoretical and empirical models are of the same order of magnitude, the theoretical model produces smaller spreads than anticipated. Though there are unresolved issues, the theoretical model suggests that most of these consumer loan markets have fully adjusted to the increased use of default risk-based pricing.

Given the effects that risk-based pricing appear to have on debt levels and access to debt, there should be important welfare implications. While very high-risk and low-risk households have benefited from these changes, high-risk households have seen their premiums increase and have changed their borrowing in response. Intuitively, welfare should change accordingly. It should be higher for those very high-risk households who gain access to debt markets. High-risk households who see their borrowing interest rates rise versus low-risk households should see a relative drop in welfare.

II. Risk-Based Pricing in Consumer Credit Markets

Tremendous developments in underwriting models and substantial reductions in data storage costs in the mid-1990s decreased the costs of risk-based pricing (Bostic, (2002)). However, certain changes in consumer credit industry practices spurred these technological improvements. The adoption of risk-based pricing, and all the necessary investment this required, is at least in part due to changes in Community Reinvestment Act implementation and changes in pricing practices at Fannie Mae. While the CRA had been on the books since 1977, Canner and Passmore (1997) point out that interest in the act intensified in the mid-1990s. In 1995, bank regulators began implementing more stringent performance-based measures of a lending institution's compliance. A greater emphasis was placed on lending in lower income neighborhoods and to lower income borrowers. Such requirements would increase the profitability of developing a technology to lend to higher risk households.

Fannie Mae guarantees its mortgage-backed securities against default risk, taking a cut from the interest payments as a "guarantee fee" to cover this cost. In the 1980s, Fannie Mae accepted only low-risk loans, and essentially did not vary prices with risk. In 1995, however, Fannie Mae introduced an automated underwriting system that more carefully evaluates risk, and, subsequently began to vary its guarantee fee based on these evaluations. Also, Fannie Mae is now more willing to accept higher risk mortgages. In fact, by the mid-1990s both Fannie Mae and Freddie Mac emphasized the correct pricing of risk. McCorkell points out that in 1996 these institutions "made it clear that lenders who wanted to sell mortgage loans [to them] would be well-advised to include a credit bureau score as part of the loan package (McCorkell, (2002))."

In addition, Peter McCorkell suggests a lack of data prevented mortgage lenders from using risk-based pricing prior to 1995. Before the early 1990s, lenders had insufficient data on defaults (from a lack of 'bad loans') in order to rely on statistical analysis. Furthermore, he points out that until the late 1980s, mortgage lenders simply relied on their constantly appreciating collateral to moderate the costs of default rather than worry too much about the credit risk (McCorkell, (2002)). Another possibility raised in the literature is that lenders were reluctant to have interest rates vary across borrowers because of fear of lawsuits (Johnson, (1992)).

Credit industry literature suggests that by the early 1980s conventional lenders began to use credit scores to automate underwriting standards, but even in the early 1990s they simply posted one house rate for each loan type and rejected very high-risk borrowers (Johnson, (1992)). Fannie Mae's varying fee introduced in the 1990s made it more costly for mortgage providers who sold loans on the secondary market not to assign rates based on risk. In addition, along with the incentives built into the new CRA regulations and with Fannie Mae buying higher risk loans, these lenders could, and did, issue higher risk mortgages (Freeman and Hamilton, (2002)). The literature shows that lenders improved the predictive power of credit scores and began to experiment with risk-based pricing methods in the early 1990s. As a result, even conventional banks were becoming prepared to lend to high-risk borrowers (Johnson, (1992)). Soon, the new pricing technology for mortgage loans made its way into other loans types, such as second mortgages, automobile loans and credit card loans. Given the empirical results, it appears that these collateralized loans and loans that could be easily sold on a secondary market have been affected the most. Given more time, perhaps, all loan pricing will be affected.

III. Literature Review

Scholarly interest in consumer debt dates back at least seventy years, when in the 1930s and 1940s policy experts began to worry about the rising level of debt. Notably, in 1941, the National Bureau of Economic Research published a series of monographs, *Studies in Consumer Installment Financing, 1936-1941*, largely aimed to document the new consumer credit phenomenon. For the next twenty years, the main focus of consumer debt research concerned its mounting levels, rather than the specific formulation of interest rates and other loan terms.

In the 1960's, a number of studies considered the inequality of the costs of credit across classes. In general, they showed that poorer households paid more for credit (for example, Caplovitz, (1967), *Consumer Credit and the Low Income Consumer*, (1969), and Aaker and Day, (1971)). In 1961, Donald Hester presented one of the first references to a loan offer function: $F(t;u,v)=0$, where t are the loan terms, such as interest rate and loan size, and u and v are the bank and borrower attributes, respectively. Cost of funds and the like are included in u, while v includes characteristics such as credit risk. Hester assumed that through competition and bargaining, banks would end up on their offer frontiers. While he found that empirically interest rates did increase in risk, they did not seem to move with changes in u and v as much as theory predicted. Even over and above the effects of usury laws, loan interest rates remained quite inflexible, staying within a conventional range. Changes in other loan attributes, such as maturity and loan size, compensated for the inflexibility of interest rates, or, alternatively, loans were simply denied (Hester, (1967)).

Much of the more recent work on costs of borrowing focuses on the related topic of liquidity constrained households, or households that face infinite borrowing costs. Some relevant examples, such as Zeldes (1989), Jappelli (1990), Runkle (1991) and Duca and Rosenthal (1993), test for the presence of liquidity constraints. Other papers examine theoretical models of the relationship between borrowing interest rates and default risk. Araujo and Pascoa (1999) present a general equilibrium model relating greater default risk to higher interest rates, but this model does not allow for straightforward empirical tests. Han studies discrimination in credit markets on the accept/reject margin. In the process, he introduces a loan offer function in a competitive loan industry, where loan repayments, given a fixed loan size, increase in credit risk (Han, (1998)). Geanakoplos has written and co-written a number of papers showing the effect of default risk on loan terms in general equilibrium (some examples are Geanakoplos (2002) and Dubey, Geanakoplos and Shubik (2003)).

Gropp et al (1997) relates levels of consumer debt to the frequency of bankruptcy and to bankruptcy laws. This paper shows that higher exemptions – leading to greater default risk – bring about both reduced availability and reduced amounts of credit to low-asset households whereas interest rates on automobile loans for these households increased. However, Berkowitz and Hynes (1998) point out that these low-asset households generally have the same exemption-status in all states, since their asset levels fall below the exemptions everywhere, so they question if this a result of bankruptcy laws. In addition, they propose an argument and present empirical evidence that larger homestead exemptions lead to lower denial rates and interest rates for mortgages. Larger exemptions induce borrowers to declare bankruptcy more often. This discharge of unsecured debt increases a borrower's net wealth. In turn, the increase in net wealth may prevent default on the mortgage or allow for a greater possibility of renegotiating the mortgage. While this argument would work for any exempt secured collateral, Berkowitz and Hynes point out that automobiles may be undersecured in bankruptcy court, so borrowers may prefer to default on auto loans rather than renegotiate.[1]

A few recent papers begin to tackle the issue of changes in borrowing costs due to technological changes in consumer loan markets. McCorkell examines whether the increased use of credit scoring has helped or hurt households traditionally underserved by the credit industry. He argues that, overall, the use of credit scoring has made judging loan applications more consistent and unbiased across the population and has helped this community (McCorkell, (2002)). Kathleen Johnson reviews the impact of increases in loan securitization on consumer loan markets and determines that it has decreased costs of borrowing on average (Johnson, (2002)).

IV. Data

The main data set used in this paper is the Survey of Consumer Finances (SCF), which contains abundant information on households' borrowing portfolios over time. The Federal Reserve Board administered the triennial SCF with the cooperation of the Department of the Treasury in 1983, 1989, 1992, 1995 and 1998. After 1992, the surveys were conducted by the National Opinion Research Center at the University of Chicago. Unfortunately, the 1986 survey used a different methodology from the other surveys, so it must be excluded from this analysis. The SCF attempts to provide a picture of the distribution of assets, liabilities, income, and use of financial institutions and instruments across households in the United States. Numbers of families surveyed were as follows: 1983 - 4,103, 1989 - 3,143, 1992 - 3,906, 1995 - 4,299, and 1998 – 4,305 for a total of 19,756. In this paper, agent, family, and household will be used interchangeably, but the definition of the survey unit is closest to the U.S. Bureau of the Census definition of the term "household". A notable feature of the survey is that it over samples relatively wealthy households. This is important to get an accurate representation of wealth holdings in the U.S. since the wealth distribution is so skewed. The Federal Reserve Board provides sampling weights that re-weight the survey population to correspond to the U.S. population both by geographic area and, more closely, by income distribution. These weights are used in measures of first and second moments using the SCF data.[2]

General results of the SCFs are discussed in a series of papers in the Federal Reserve Bulletin (Kennickell et al (2000), Kennickell et al (1997), Kennickell and Starr-McCluer (1994), Kennickell and Shack-Marquez (1992) and Avery et al (1987)). The Board's definition of net worth and income are used,[3] as well as the Board's imputations for missing data. In addition, the nominal dollars are reported in 1998 values using the consumer price index.

The SCF contains data on a broad array of collateralized and non-collateralized loans and their interest rates. The loans considered in this paper are first and second mortgages, automobile loans, general consumer loans, credit card loans and education loans. All loans considered here are active in the month of the survey, including credit card loans; credit card balances are only defined as loans when the household is carrying the balance long enough to pay interest on it.[4] In addition, if households have multiple loans in a category, the highest interest rate is used in the analysis, and the dollar amounts relevant for the multiple loans are summed. For example, it is not uncommon for households to have multiple automobile loans at different interest rates. All data on automobile loans are aggregated to get one auto loan at the highest interest rate. This

[1] The implications that this argument has for how exactly the risk of bankruptcy should relate to the interest rate are unclear. For example, this may reduce the interest rate premium that those with high-risk of bankruptcy must pay.
[2] Deaton (1997) makes a convincing argument that weights should not be included in models when parameters do not vary across the population. In contrast, in models using SCF data, we assume that coefficients are constant across the population.
[3] Net worth consists of a family's financial portfolio (including IRAs, most thrift plans, and the cash equivalent of life insurance policies), business and house equity, and vehicles, less debt.

interest rate can then be thought of as the marginal rate at which a household could borrow one additional dollar to finance an automobile. Summing all the automobile loans for ease of estimation, this is clearly the relevant interest rate to consider. The SCF also contains data on a broad array of household characteristics, both demographic and financial.[5]

Table 1 shows the total observations across the five years of data for the various loan categories that were considered. In addition, the mean and standard deviation of the interest rate for 1998 loan originations years are reported for each loan. Overall, the results are just as one might expect. First mortgages have the lowest interest rates while credit card rates are the highest, and other consumer loan rates are the second highest.[6],[7] Interestingly, education loan rates are remarkably low with a standard deviation more in line with the collateralized loans. This possibly reflects the government's involvement in this market or that this loan – more than other non-collateralized loans – is dedicated to a productive purpose. Additionally, government-backed education loans cannot be discharged in bankruptcy proceedings.

Because the SCF surveys before 1998 do not report if a household has declared bankruptcy, an important indicator of default risk needed to understand interest rate determination, the Michigan Panel Study of Income Dynamics (PSID) is used to supplement the SCF. The PSID is a longitudinal data set of US households dating back to 1968. In 1996, the PSID asked households if they had ever filed for bankruptcy in the past, and if they had, what year(s). The PSID includes information on the level of unsecured debt and the value of non-housing wealth in only 1984, 1989 and 1994.[8] In order to include net worth and debt in the analysis, only these years are used. Aside from bankruptcies, every variable from the PSID used in this paper has a close counterpart in the SCF. The total number of distinct households across the three years of data with bankruptcy data is 7,665. Among these households, the total number

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[4] One drawback that Gross and Souleles (2001) point out in the SCF is that respondents underreport credit card debt. This could pose a problem to the credit card result if underreporting is significantly correlated with risk, and this correlation changes over time.

[5] Unfortunately, the SCF does not contain certain data that would be helpful in evaluating loan terms. For example, post-1983, the public dataset does not report the respondent's state, only their very broad region of the country. Additionally, the data on mortgages does not include any prepayment information or points paid.

[6] Other consumer loans include loans for household appliances, medical bills, loans from individuals and others. When these loans are collateralized, the collateral is less secure that an automobile or a house. Generally, the borrower keeps possession inside the house (making seizure difficult) and value of the asset is quite variable. Indeed, repossession of even major home appliances is quite rare (Capovitz, (1974)).

[7] I get the same qualitative results if I do not condition on the year of loan issuance and instead look at moments for the 1998 survey year.

[8] The Latino Supplement of 1994 is not used in this analysis.

of bankruptcies across all years prior to 1996 is 502. This reflects a slightly lower rate of occurrence than that observed in the US population.[9]

V. Empirical Analysis

A. General setup

The primary goal of this empirical analysis is to estimate the role default risk plays in interest rate determination and see if that role has changed over time. Taking into account the nature of the data, I must account for selection bias. After all, the SCF only reports interest rate data for households who successfully secure loans. Without accounting for selection bias, results will be inconsistent. As an illustration, increased education may be associated with reduced default risk. In this way, higher education may reduce interest rates for households. Conversely, more education may increase the likelihood of receiving a loan due to greater familiarity with financial markets or reduced search costs. Because some randomness in interest rates may cause identical people to face different interest rates, we might suppose, for example, that interest rates are lower for those with loans than for otherwise identical people without loans. As a result, the remaining distribution of interest rate shocks for households with loans is affected. As education also affects which households obtain loans, simply regressing interest rates on education will misrepresent education's influence and is inconsistent.

To simplify the analysis, assume a household requests a certain loan amount, A, with a given maturity, T, and a given level of collateral, which leads to recovery rate of the loan balance in default, l. These loan attributes are then simply inputs into the model. As a function of these attributes, as well as the lender's discount rate, o, any fixed costs, f, and of course the borrower's default risk, d, the lender then offers an interest rate. The household accepts the loan if the offered interest rate is lower that the household's reservation interest rate, R, given the loan attributes and the household's characteristics, P. Note that d may also affect R, as d is a function

[9] The PSID underestimates the frequency of bankruptcy. For example, the filing rate in the PSID was 0.15% of the total population in 1984 and 0.59% in 1995. To compare to national data, the filing rate was 0.33% in 1984 and 0.88% in 1995 (Fay et al (1998)). Andreas Lehnert points out that national statistics include repeat chapter 13 filings separately while households may consider these as one filing. Technical reasons commonly lead to multiple Chapter 13 filings. Additionally, the low-income subsample is included in the data since this population is of interest in studying consumer lending. Perhaps if it were removed bankruptcy rates would match the total population more closely.

[10] As the objective of this approach is to measure the influence of borrower's observable risk, issues of asymmetric information are not considered. However, strategic default may play an indirect role if lender's use observable borrower's characteristics to predict the likelihood of strategic default which is incorporated into overall default risk. Due to data limitations, prepayment risk is not considered.

of a subset of P.[10] Without observing the reservation interest rate, we can still infer that it is lower than or equal to the offered interest rate for those consumers who have positive loan balances. To formalize:

$$R_i(A,T,l,P_i) - I_i(A,T,l,d_i,o,f) = H_i\beta + u_i,$$
$$w_i = 1 \;\; if \;\; R_i - I_i > 0, \;\; w_i = 0 \;\; if \;\; R_i - I_i \leq 0,$$
$$\Pr ob(w_i = 1) = \Phi(H_i\beta) \;\; and \;\; \lambda(H_i\beta) = \frac{\phi(H_i\beta)}{\Phi(H_i\beta)}$$

$R_i(A,T,l,P_i)$ is the reservation interest rate, and I is the interest rate offered by the lender. H_i, a vector of characteristics, helps predict whether the loan is observed for household i. The interest rate function $I_i(A,T,l,d_i,o,f)$ is subscripted i to allow for an idiosyncratic individual specific shock, ε_i.

$$I_i = \mathrm{X}_i\gamma + \varepsilon_i, \;\; observed \quad when \;\; w_i = 1$$
$$and \;\; u_i, \varepsilon_i \sim bivariate \;\; normal \;\; [0,\; 0,\; 1,\; \sigma_\varepsilon,\; \rho]$$
$$E[I_i \mid \mathrm{X}_i, w_i = 1] = \mathrm{X}_i\gamma + \rho\sigma_\varepsilon\lambda(H_i\beta)$$

Here, X_i is a vector of characteristics that help predict loan interest rates, I. X includes direct measures or proxies, where necessary, for *A, T, l, d, o* and *f*.[11] Note that this model essentially does not allow for a rejection by the lender. However, we can consider a loan rejected any time $R_i - I_i \leq 0$.[12] Given the proposed relationship between the predictions of which households carry a loan and what the interest rate is, the hypothesis is that ρ is negative.

H should contain variables that determine whether or not a household carries a particular loan. As a result, both supply and demand variables should be included. On the supply side, *H* includes variables that help predict when a firm may deny a loan. For example, default risk should play a role here. Without taking a definite stand on the nature of this role, *H* includes second-order polynomials of default risk. To account for demand, other financial and demographic characteristics, P_i, that might predict whether a family holds a loan are included: an age polynomial, marriage status, the number of children, whether the family has a checking

[11] The theoretical model of interest rate determination discuss in section VIII helps to justify the assumption of linearity in *X*.
[12] For example, if a lender at least knows the upper bound for a household's reservation wage, it may choose to simply reject a loan rather than offer an interest rate above this upper bound.

account, education, log of income, net worth, level of assets, and variables which reflect borrowing attitudes (which are discussed in detail below). Race is also included in *H* for two reasons. First, it is possible that racial status reflects differences in preferences and attitudes towards borrowing. Second, while this is not the focus of the paper, lenders may discriminate in access to loan markets (see Edelberg (2002)).

If markets are competitive, interest rates should only vary for reasons captured in $i=i(A,T,l,d,o,f)$. Lenders should not be able to exploit variations in household demand. For example, if an agent's higher demand for debt induces him to carry many loans, he should be a higher risk than an agent should be with a low demand for debt, and he should receive a higher interest rate only because of his higher default risk.

I must find at least one variable in *H* that is not in X, so as to not depend on the functional form to identify the model. Certainly, exogenous characteristics such as age, education, wealth and income should be included in both in some way, even if they only influence interest rates through their effect on households' default risk. On the other hand, the SCF contains information on household's opinions about borrowing. For example, households report whether they consider borrowing to be good, bad, or simply okay or whether they believe borrowing in certain circumstances is acceptable such as a loss in income, to buy a house or an automobile. These attitudinal responses are included in *H* and excluded from X since the information is private to the household and thus cannot be used by the bank in determining an interest rate.

While we would expect that a family that reports it is acceptable to borrow for education expenses may be more likely to hold an education loan, these attitudinal variables contain little information if they simply reflect each household's loan portfolio precisely. Fortunately, they do not. Table 2 contains a breakdown of the percentage of households that hold certain types of loans and those that report which type of borrowing is acceptable.

While there is clearly some correlation between attitudes and debt holdings, the attitudinal variables contain additional information. Overall, the attitudinal variables do not simply reflect current borrowing habits. For example, only 34% of those who agree that it is acceptable to hold an automobile loan actually do hold one. Other robustness checks confirm that these attitudinal responses are not simply proxies for variables seen by the lender and not contained in the data sets.[13]

Of the inputs which construct $i=i(A,T,l,d,o,f)$, some are straightforward in a reduced form equation. For example, the discount rate, o, which is dependent on the cost of funds, is presumed constant over a year and is captured by year dummies.[14] In as much as fixed costs should only vary across loan types, the influence of fixed costs per loan, f, will be seen through the different effects of varying the loan amount, A. Maturity, T, does not generally vary meaningfully within a loan type, and was often found to have no real significant effect on interest rates. For example, nearly 60% of automobile loans have maturities between four and five years. T is excluded from the empirical work; though this issue may be revisited in future work.

For non-collateralized loans, l should be close to constant within a loan-type. For example, credit card lenders use roughly the same expected recovery ratio for all loans. In the recent congressional debate regarding changes in the bankruptcy laws lenders often argued that l is zero. Most likely this is an overly pessimistic view. Lenders can garnish wages and obtain property liens if a borrower is in default. Garnishment is limited however; the Consumer Credit Protection Act of 1968 allows lender to garnish only 25% of a household's wage, and less if income is low (Candilis, (1976)). Indeed, some states prohibit garnishment altogether (Sullivan et al, (1989)).

Since garnishment and property liens are costly to obtain, requiring relatively extensive legal effort, liens are more commonly used as a threat and possible punishment, rather than a method of recouping losses. Only 4% of all claims at the time of bankruptcy were the subject of lawsuits (Winton, (1998)). Still, while l may be small, it is likely above zero. In any case, if its expected value is constant for each type of non-collateralized loan, its varying effect will be loaded into the constants.[15]

For collateralized loans, accounting for l in each type of loan is not as straightforward. For example, l will be higher for a loan that is 100% collateralized versus one that is only 50%

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[13] In the end, numerous variables are included in H but not in X, so that the demands on the attitudinal variables as appropriate instruments are less than they might be. However, robustness checks were still done. All the significant attitudinal variables from the probits were included in their respective regressions. In all cases, a majority of the coefficients were insignificant – in most cases an overwhelming majority.

[14] This should in part reflect the required rate of return to those supplying loanable funds. For example, Ausubel (1991) finds that credit card issuers earned between 3 and 5 times the ordinary banking rate of return from 1983 to 1988. My methodology imposes no specific rate of return on each type of loan, but does take these returns as the result of competitive markets.

collateralized. While a creditor can still seek a lien against a borrower if there is a deficiency after repossession, the deficiency is treated like an unsecured loan. In these cases, the secured lenders are as unlikely to pursue liens as the unsecured lenders above. After repossession, creditors rarely go after deficiencies, and generally recover no more than 5 to 15% of the deficiency when they do (Winton, (1998)). To keep things simple and yet capture the effect of varying l, equity in the relevant loan collateral is included as a predictor of interest rates.

This brings us to estimating default risk, d. While perfect data would include each household's credit score, this is unavailable. However, the SCF does contain data on actual delinquencies that will help generate a proxy for the score. Whether or not a household is late on payments may be a source of substantial costs to a lender. If a household is late in making payments, a lender may need to flag the account, make contact with the household, perhaps begin to partially write-off the debt, and eventually send (or sell) the loan to a collection agency. The SCF reports whether respondents have been more than sixty days late on a loan payment within one year of the survey date. Since the actual delinquencies occur in calendar time after the loans are issued, lenders would not have data on these actual delinquencies when setting interest rates. This analysis estimates this one form of default risk by including predictions of probabilities of being delinquent on payments, rather than on actual data of late payments.[16]

Another reasonable method would include actual rather than predicted delinquencies. First, rational expectations suggests that lenders should get these predictions right on average. Second, since it is altogether possible that lenders have different and better financial and demographic data than what is contained in the SCF, lenders may have much better predictions of this form of default risk than what this analysis can produce. In the end, estimations are conducted using both predicted and actual delinquencies, and large differences are noted, though results are generally robust to either specification.

Of course, being delinquent on payments is only one important source of default risk. Lenders are also concerned with outright bankruptcy. Unfortunately, the SCF before 1998 contains no bankruptcy data. On the other hand, the 1996 supplement to the PSID does contain data on whether and when households declared bankruptcy. This method of including predicted

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[15] The possible complication that l may be in part a function of d – for example, a priori high-risk people in default may be more difficult to collect from than low-risk people in default – is not considered here.

[16] As will be clear in the empirical analysis, a good bit of the information in late payments is indeed used by lenders in pricing interest rates at loan origination. For every loan considered, average rates paid are higher for those who made late payments versus those who had no late payments. Raw differences are a low of 0.2 percentage points for education loans to a high of nearly 2.5 percentage points for automobile loans.

bankruptcy rates from the PSID follows from Jappelli, Pischke and Souleles (1998). Jappelli et al need predictions of which households are liquidity constrained in their analysis of PSID data. They estimate the probability of being liquidity constrained in the SCF and then impute probabilities in PSID respondents by using the estimated model and similar characteristics. In contrast, I need predictions of which households are likely to declare bankruptcy in analyzing SCF data. The plan is to estimate a model of future bankruptcy in the PSID and then use these coefficients to impute probabilities in the SCF. The necessary correction of the standard errors using this approach is discussed in section XIII.

B. Bankruptcy

Bankruptcy is measured as an indicator variable. It takes a value of one if the respondent declared bankruptcy within two years after the three wealth surveys.[17] On the other hand, this structure of the data allows two forms of bankruptcy risk to be estimated with a probit. First, a probability of declaring bankruptcy will be predicted for those households with debt as of the survey date. This conditional bankruptcy will be relevant for lenders assessing interest rates for loans, i.e. this measure will be included in *X*.

Second, some measure of default is to be included in *H*, the vector of characteristics predicting whether a household holds a certain loan. This measure should allow for households with zero debt. In this case, a probability of declaring bankruptcy will be predicted for all households, whether or not they hold debt as of the survey date. This is possible because a full 14% of bankruptcies that are declared within two years of the survey date are originated by households with no debt as of the survey date. In other words, zero current debt does not imply zero future bankruptcy risk. This unconditional bankruptcy measure will reflect the predictive power of certain financial and demographic characteristics aside from debt levels.

In selecting the household characteristics that belong in a bankruptcy model, quite a bit of research has been done in this area; chosen characteristics for the conditional bankruptcy risk are year, a second order polynomial in age, lack of a checking account, the natural log of income, whether a household is self employed, home ownership status, whether the ratio of unsecured debt to income is greater than two, net worth (with negative net worth set to zero), non-collateralized debt, if a family head is unemployed, race, an education class variable taking five

[17] Unfortunately, the range between the last wealth survey in 1994 and the latest PSID data used here is too short to allow for a longer window.

values[18], and whether the head is a single parent. For the unconditional estimation, measures of debt and home ownership status are removed and asset levels are included. A brief discussion of the research that supports these choices of characteristics, within the limitations of the data, follows.

Sullivan et al (2000) shows that people in bankruptcy are generally middle class. Ages of filers range from 20 to 83, with an average of 36, though 10% of filings are from those over age 55. The bankrupt household has more education than average. Of problems people report as the cause of bankruptcy, two-thirds offer job-related reasons, such as loss of wage, one-fifth report medical problems and expenses, one-fifth report family problems such as divorce and the remaining households give an account of creditor problems and housing costs. Bankruptcy has become more frequent over time. In 1991, there were 812,685 filings; by 1996, there were over one million; and by 1997, there were 1.4 million filings. Also, women filing has become more common, and by 1991 more single women filed than single men.

Credit card debt is the most frequently listed type of debt. Including retail store cards, credit card debt was reported by 83% of filers in 1997. At the mean, these filers had a ratio of credit card debt to income of 0.77. (The median is lower at 0.47.) Sullivan et al (2000) goes on to show that people tend to declare bankruptcy when the ratio of unsecured debt to income approaches 1.5. At its mean, this ratio is over two.

Sullivan et al (1989) reveals that among filers, income is two-thirds of the national average, and assets are 30% of an equivalent household not in bankruptcy. Home-ownership is only slightly lower than the national average. While mortgages are roughly the same size among bankrupt households and the nation, non-mortgage consumer debt averages were nationally $4,500 and $20,600 for bankrupt households in the 1980s. Additionally, home ownership may indirectly lead to bankruptcy as families default on all other debts in order to have the resources to pay the mortgage.

Filers are disproportionately self-employed (20% of total filers versus 7% at the national average), though to distinguish among occupations does not help predict bankruptcy. Perhaps surprisingly, filers' unemployment is virtually identical to the national average, though unemployment may lead households to bankruptcy. To explain this contradiction, bankruptcy helps to shield future income, so without the clear prospect of income, bankruptcy is far less

[18] The five values for education are assigned for 'less than high-school,' 'high-school,' 'some college,' 'college degree,' and 'post-college education.'

attractive. As a result, households have a reason to wait for employment before filing. Finally, Sullivan et al, (1989) argues that medical debt leads to only 1-2% of bankruptcies.

Domowitz and Sartain study the causes of bankruptcy. In brief, they find that home ownership discourages bankruptcy, while having a medical debt to income ratio over 2% encourages bankruptcy. Credit card debt and being single are also big predictors of bankruptcy. Income by itself has little predictive value (Domowitz and Sartain, (1999)).

Fay et al (2002) shows that the likelihood of filing is positively related to the financial benefit of bankruptcy. Financial benefit takes into account unsecured debt and non-exempt wealth, and is always nonnegative. Households with increasing non-exempt wealth should be less likely to declare bankruptcy as they have more to lose. In this sense, households with varying degrees of negative wealth net of secured debts should only consider debt levels, and not wealth, when making the decision to file. To capture this effect, and also reflect some of the other research mentioned above, positive net wealth and unsecured debt are included as predictors of bankruptcy.

Fay et al also point out that the effect of home ownership is ambiguous. While home ownership may lead to bankruptcy for the reasons above, as well as to delay foreclosure, it may also deter bankruptcy if the household has equity in the house over and above the exempted level. The authors also argue that bankruptcy rates should first increase with age and then eventually decrease as households tend towards net saving. Year dummies are included to account for the common belief that bankruptcy has exogenously increased over time (i.e. Gross and Souleles (1999)). One variable that the research doesn't directly point to is the lack of a checking account. This is to proxy for financial expertise, as a household without such basic financial experience may not be able to navigate the bankruptcy laws.

Race should be included as a potential predictor for two reasons. First, realistically I need to allow for differences in the way households can gain access to the financial system – for example, the legal system may make it more difficult for minorities to declare bankruptcy. Second, race may be a proxy for important financial and demographic omitted variables that the lender observes but are not in the data sets. Given that race is significant in predicting both measures of default risk, bankruptcy and delinquent payments, surely one or both of these explanations are at work. Further tests for discrimination are presented in Edelberg (2002). Note that I include predictors in addition to race that are also illegal for lenders to use in assessing default risk – age and marriage status. Johnson (1992) points out that lenders discriminate by finding usable variables that are highly correlated with variables they are not allowed to legally use.

The results are reported in Table 3 and Table 4. In all cases, the hypothesis of coefficients changing over time was tested. In the end, the only time interacted coefficients that were kept were those for the variables with coefficients significantly changing over time. Overall, the coefficients for both the unconditional and conditional estimations are in keeping with what is known about bankruptcy.

A few highlights are discussed here. As expected, the year dummies show that the probability of bankruptcy has generally increased over time. An increase in the natural log of income increases the probability of declaring bankruptcy. In other words, an increase in income increases the probability of bankruptcy, but at a decreasing rate. Again, the probability of declaring bankruptcy should increase in the lower regions of income since bankruptcy offers a way to shield income from garnishment. As income increases, however, the advantages of bankruptcy increase, but the need to declare bankruptcy decreases.

Home ownership is significant and positive in the conditional estimation, with a decreasing coefficient over time – turning negative by 1994. Interestingly, this follows the hypothesis in Fay et al that home ownership has an ambiguous effect on bankruptcy probability. Reflecting the fact that bankruptcy is often used as a way to shield future earnings from garnishment, being unemployed reduces the chance of bankruptcy by 0.28%. Being Black reduces the probability of bankruptcy by 0.13%, though the coefficient is only significant in the unconditional estimation. This may be capturing the common finding in research that Black households are less involved in the formal financial sector. For education, the point estimate suggests that greater education reduces the probability of bankruptcy, though the effect is only significant and large for the conditional estimation. Bankrupt households often have more education than the average household, so education may have two offsetting effects (Sullivan et al (2000)).

When this model is used to impute probabilities of bankruptcy in the SCF data, predicted bankruptcies are calculated with year dummies as close as possible to the wealth survey dates. Other explanatory variables are carefully matched from both surveys, including net worth. Predicted bankruptcy rates from both the SCF and PSID samples across all the years of data are summarized in Table 5. The two samples do not give dramatically different pictures of predicted bankruptcy rates. Note that for the vast majority of the populations, the predicted probability of bankruptcy within the next two years is quite small; the 90th percentile household with debt in the SCF still has only a 2.3% predicted probability of declaring bankruptcy.

A useful method of organizing households is by riskiness according to their quantile of conditional probability of declaring bankruptcy where the first quantile of probabilities is the least risky and the fifth quantile is the most risky. Table 6 reports the average values for a number of financial and demographic characteristics by quantile. Averages and quantiles and computed across all years of data. For example, the table shows that as households tend to be riskier, age, income and net worth tend to fall, and the probability of not having a checking account and being a single parent tend to rise.

C. Late Payments

Predictions of the late payment indicator from a probit model use the same characteristics as those used to predict bankruptcy. Much less research has been done in the area of delinquency than in bankruptcy, but certainly the insights from bankruptcy research should carry over. As a result, I use the predictors of bankruptcy here as well. This has the benefit of making the late payment results directly comparable to those for bankruptcy.

In the case of bankruptcy, I was predicting an event that either happened, or did not happen, for all households in my sample. In contrast, I only have data on whether households with loans were late on payments. To account for this possible selection bias, I will use a similar approach as that used to predict loan interest rates; specifically, the attitudinal variables will ensure identification. Again, I include year interaction terms for coefficients that change significantly over time. As one would imagine, being late on payments is a higher probability event than declaring bankruptcy – over the five years of raw data 12.4% of the respondents have been late. Results of the selection probit are reported in Table 7.

A few highlights from the probit are discussed here. The probability of late payments increases from 1983 to 1989, decreases through 1995, falling below its 1983 level, and then increases a little. As age increases, the contribution to the probability of being late first increases up to age 29 and then falls. The contribution eventually turns negative at an age of 58. Home ownership negatively predicts delinquencies, with its effect generally increasing over time, when significant. The variable reflecting a high ratio of unsecured debt to income is also helpful in predicting late payment (and the sign is as expected). Once the probability of late payments is estimated for each household, these probabilities can be used to measure this one type of important default risk.

While not the focus of this research, the selection equation deserves attention. This equation essentially predicts the inclusion of debt in the household's portfolio, as delinquencies can be measured for households with positive debt. The raw fraction of households with debt increases through 1995 and then falls slightly in 1998. On the contrary, conditional on the household characteristics, the probability of positive debt falls through 1995 and then increases. Reflecting both models of consumption smoothing and borrowing constraints, an increase in age increases the probability of debt (at a decreasing rate) through age 28, when an increase in age starts to predict a lower probability of debt. Age's contribution remains positive though 57.

Aside from the attitudinal variables, the remaining explanatory variables are all significant except for race and single parenthood. Generally, we see that overall financial health and stability leads to the inclusion of debt, in accord with the discussion in Maki (2002). Not having a checking account, being self-employed and unemployed have negative contributions while income and education have positive signs.

Five of the seven attitudinal variables are significant (all except for indicators that *borrowing is acceptable for furs and jewelry purchases* and *borrowing is acceptable for education expenses*). The more acceptable borrowing is to a household, the greater the probability of positive debt. One of the more constrained measures of borrowing attitudes, *borrowing is okay for a cut in income* actually has a negative sign, suggesting that respondents who feel this way may only use borrowing for infrequent smoothing of large negative income shocks. One of the least constrained measures, *borrowing is okay to finance a vacation*, has a positive coefficient, as does *borrowing is okay to purchase an automobile*.

Predicted probabilities of late payments for the entire SCF sample – conditional on holding debt – are reported in Table 8. Note that the correlation between predicted bankruptcy and late payments is only 0.35, reflecting the distinct measures of default risk that these two predicted probabilities represent.

D. Putting it all together

Estimated probabilities of SCF households delinquencies are notated $g\left(d_i, \hat{\theta}_M\right)$ where d_i are observable characteristics for household i and $\hat{\theta}_M$ is the vector of late payment estimation coefficients in sub-section C. Estimated conditional probabilities of bankruptcy for these households are notated $f_c\left(z_i, \hat{\theta}_m\right)$, and unconditional probabilities are $f_{uc}\left(z_i, \hat{\theta}_m\right)$, where z_i only differs from d_i with respect to minor differences in the formation of year dummies and $\hat{\theta}_m$ are the coefficients from the PSID bankruptcy estimation in sub-section B. Together, $f\left(z,\hat{\theta}_m\right)$ and $g\left(d,\hat{\theta}_M\right)$ reflect a household's default risk, *d*.

This methodology requires one important qualification. These measures only offer a snapshot of a household's default risk at the survey date. In reality, a lender must forecast a borrower's possibly changing *d* over the entire course of the loan. The ideal data set would include what the lender observes at the time of the loan, and what the lender predicts for the borrower's attributes over the course of the loan – since these lead to a lender's predictions of the borrower's future default risk. Thus, the contribution of this series of default risks to the interest rate at loan origination would become apparent.

While I only have a cross section of borrowers attributes, the fact that my data arise from after loan origination does not pose a fundamental problem given two alternative assumptions. Either, I can rely on the persistence of household demographic and financial characteristics, or I can assume perfect foresight on the part of the lenders with regards to borrowers' future characteristics over the life of the loan. In either case, I am free to use household characteristics at the time of the survey to estimate concurrent default risk. This estimate of default risk should be relevant when interest rates are set at loan origination.[19] To the extent that my assumptions do not hold, the explanatory power of default risk as it is measured here will be reduced.

An estimate of the contribution of both measures of default risk to interest rate variation before and after 1995 is required to test whether or not the nature of pricing risk changed during the mid-1990s. To do this, each measure of default risk enters on its own and interacted with an indicator variable that takes a value of one if the loan was originated 1995 or later, namely I_{95}. The effects of other variables besides those measuring default risk are kept constant over the sample. This methodology allows us to easily see if default risk's contribution significantly changed in the mid-1990s.

In the notation of sub-section A:

$$\mathrm{X}=\left[x \;\; f_c\left(z,\hat{\theta}_m\right)I_{95} \;\; f_c\left(z,\hat{\theta}_m\right) \;\; g\left(d,\hat{\theta}_M\right)I_{95} \;\; g\left(d,\hat{\theta}_M\right)\right];\; H=\left[h \;\; f_{uc}\left(z,\hat{\theta}_m\right) \;\; f_{uc}\left(z,\hat{\theta}_m\right)^2\right]$$

Given the linearity in $I_i = \mathrm{X}_i\gamma + \varepsilon_i$, this approach depends on the assumption that lenders are risk neutral or are diversified enough to behave as if they are risk neutral. As banks only care about expected return, high-risk borrowers are not penalized for their contributions to the portfolio's variance, only the portfolio's expected return. The potential role of the risk aversion of banks in further increasing the rates paid by high-risk borrowers is left to future work.

As predictors of a loan's interest rates, x includes loan origination year dummies, loan amounts, and equity in collateral where relevant. X contains k variables in all. Note that H only includes unconditional bankruptcy risk as a measure of default risk. Since the delinquency measure is conditional on holding a loan, its inclusion in H would in inappropriate. Predicting the inclusion of the loan in the household's portfolio, h includes survey year dummies, a second-order polynomial in age, education, log of income, marriage status, number of dependents, net worth, value of assets, whether the household has a checking account, race, and the attitudinal variables discussed in Table 2.

Risk-based pricing will be evident by how much interest rates change with a 0.01 increase in bankruptcy risk (i.e. changing from a risk of 0.03 to 0.04).[20] Additionally, as defined below, the default risk premium spread also helps to measure the extent of risk-based pricing:

$$\begin{aligned} premium\ spread = {} & \left[\gamma_{k-3} f_{c,R}\left(z,\hat{\theta}_m\right) I_{95} + \gamma_{k-3} f_{c,R}\left(z,\hat{\theta}_m\right) + \gamma_{k-3} g_R\left(d,\hat{\theta}_M\right) I_{95} + \gamma_{k-3} g_R\left(d,\hat{\theta}_M\right)\right] \\ & - \left[\gamma_{k-3} f_{c,L}\left(z,\hat{\theta}_m\right) I_{95} + \gamma_{k-3} f_{c,L}\left(z,\hat{\theta}_m\right) + \gamma_{k-3} g_L\left(d,\hat{\theta}_M\right) I_{95} + \gamma_{k-3} g_L\left(d,\hat{\theta}_M\right)\right] \end{aligned}$$

where $\gamma's$ are the coefficients from the interest rate equation in the selection model estimation. In actual premium calculations, only $\gamma's$ significant at the 90[th] percentile are used. Note that the risk premium is either post- or pre-1995 depending on the value of the indicator function, I_{95}. R and L define averages of $f_c\left(z,\hat{\theta}_m\right)$ and $g\left(d,\hat{\theta}_M\right)$ for high- and low-risk subsets of the entire population. These subsets are calculated by conditional bankruptcy probabilities: the highest- and lowest-risk groups are the 20% most and least likely to declare bankruptcy, respectively. These groups remain fixed across all risk premium definitions.

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[19] I am indebted to Professor Gary Becker for pointing out this argument.

[20] Given linear interest rate functions, the change in the interest rate per a 0.01 increase in risk is constant. If we were to allow for risk aversion among banks, we might we interest rates as an increasing function of risk.

VI. Empirical Results

A. Evidence of Changing Default Risk Premium Spread

To some extent, evidence of the increased use of risk-based pricing is evident even without extensive empirical modeling. Indeed, Table 9 shows that variances in consumer loan interest rates generally increased – often significantly – from 1989 to 1995 to 1998, with interest rates dated from loan origination. For these three years of data standard deviations of monthly prime interest rates were roughly similar and actually decreased from 1995 to 1998. For example, standard deviations of 30-year fixed Treasury bond rates were 0.50, 0.57 and 0.36 in 1989, 1995 and 1998 respectively. Raw averages of actual interest rates as a function of conditional bankruptcy are also informative. In general, raw premium spreads are larger post-1995 versus pre-1995. As reported in the table, the spreads are taken from interest rates averaged for a two-year period in order to have a reasonable number of observations for each risk group. Under the heading 1989 spreads, interest rates are from 1988 and 1989. For 1995, rates are from 1995 and 1996, and for 1998, rates are from 1997 and 1998. Standard deviations for these years are again similar for monthly interest rates, though in this case prime rates are more variable in 1997 to 1998 then in the prior years.[21]

Moving on to the results from the selection models, Figure 1 shows predicted interest rates plotted against conditional bankruptcy risk pre- and post-1995 loan origination dates. For each loan type, interest rates are predicted by the significant measures of default risk and other significant variables are set to their mean values. The effects of year dummies pre- and post-1995 are averaged so that the predicted zero default interest rate reflects the average discount rate over the period in question. 90% confidence bands are also reported.

As a basic check of the methodology we can see that none of the interest rate lines is downward sloping – which would suggest that higher risk households are predicted to receive *lower* interest rates. The critical point in interpreting these graphs is that in almost all cases the slopes are becoming steeper over time. The only exception is other consumer loans, which saw no change in the default risk premium post-1995. In the cases of the other two unsecured loans, credit card and education loans, the pre-1995 line is flat, suggesting that there was no significant default risk premium in this period.

[21] These raw variances and spreads should certainly be interpreted with care since besides loan origination year much is not controlled for. However, first mortgages are limited to 30-year fixed-rate mortgages, since changes in

The increasing steepness of the slopes can be summarized by measuring how much interest rates change with an increase of 0.01 in bankruptcy risk. This change more than doubles for first mortgages, going from 0.16 to 0.38 interest rate points. The change is up nearly five times for second mortgages and more than doubles for automobile loans. As is clear from the figure, there is no change in the slope of the interest rate curve for general consumer loans. Credit card and education loans go from zero slopes to changes in interest rates of 0.48 and 0.30 respectively.

An additional quick way to summarize the information in these graphs is to look at the default risk premium spreads. Table 10 shows these for pre-1995 and post-1995. All three spreads for secured loans at least double over the sample. The differences in the spreads are significant at a 95% confidence level for first mortgages and automobile loans and at 90% for second mortgages. The results are mixed for unsecured loans. While the spread is positive but unchanged over the sample for general consumer loans, there is a statistically significant spread for credit card loans and education loans only post-1995.[22]

Before an interpretation can be made of these results, first note that they are quite robust. Coefficients from the regression portion of the selection models are reported in Table 15, though the origination year dummies are suppressed for readability. The coefficients from other possible methodologies are also reported for comparison. As mentioned in section Late Payments, an argument can be made for using actual late payments rather than predicted late payments in the interest rate equation estimation. Overall coefficients' values and significance for unchanged variable are stable. Default risk spreads computed from these coefficients reflect this. While spreads are generally smaller than in the base model, over time they still increase significantly for all secured loans and credit card loans (well over doubling for both mortgage types). As in the base model, spreads for general consumer loans are unchanged, though education loans now have no significant spread both before and after 1995.

Table 12 also shows the results from using 1996 as the cutoff year rather than 1995. In the case of credit card loans, 1998 is used since there is no credit card data in between survey dates. Secured loan spreads are virtually unchanged and again at least double over time. The

raw variances in particular are otherwise difficult to assess. Note that credit card rates are unavailable for 1989, so in the place of 1989, 1983 data are used.

[22] Even if the pre-1995 spreads for credit card loans and education loans are calculated using insignificant coefficients, these spreads are still close to zero at only 0.03 and 0.18, respectively.

results for general consumer loans and education loans show no change. Credit card loans show a spread both before and after the cutoff year, with the spread doubling over time.

Finally, results from models using only conditional bankruptcy and delinquency predictions in turn are reported. Here we see that while the models generally reflect the base model's results, there is value-added from using both measures of default risk. With no conditional bankruptcy included, spreads are roughly unchanged for secured loans. For unsecured loans, the levels of the post-1995 base model spreads are reached pre-1995, with no significant change after 1995. With no predicted late payment measure included, only the first mortgage and credit card spreads are truly consistent with the base model. second mortgages work well post-1995, but pre-1995 there is no significant spread. On the other hand, automobiles show no significant change from the pre-1995 spreads. Finally, other consumer loans and education loans have no significant spread at any time.

The full results of the probit portion of the selection models are shown in Table 13. Here we see that the null hypothesis of no selection bias is not rejected for credit card loans and education loans. Both of these estimations were redone using simple robust regressions. The qualitative results are unchanged. Default risk premium spreads for credit card loans increase while education loans show no change.[23]

Across nearly all of the models, the results for secured loans fit well into the hypothesis of lenders' increased use of risk-based pricing. Post-1995, lenders increased the risk premium assessed to the higher-risk class versus the lower-risk classes. While education loans do conform to the theory in the base model, of the unsecured loans, credit card loans are the most robustly consistent with the hypothesis. Interestingly, of the three non-collateralized loan types, credit card loans have the highest incidence of loan securitization. As mentioned in section II, the secondary market for loans may motivate risk-based pricing.

The results for general consumer loans in particular may reflect that these lenders have yet to feel the pressures that led to default risk-based pricing in the other markets. In addition, costs of default may have decreased over time for some loan types. Winton (1998) discusses how

[23] For credit card loans, one could argue that the model should exclude 1983 data. State usury laws that capped interest rates were rendered ineffective by the Supreme Court Marquette decision in 1978. These laws had the greatest effect on credit card loan rates, as most other rates were under the cap. Arguably, the credit card issuers had not entirely adapted to the decision by 1983 as many companies reacted to it by moving their operations out of state. As evidence of this, the cap in most states was near 18%, and, in 1983, 63% of credit card loan interest rates fell between 17% and 19%. In contrast, in 1995, the highest frequency 2 percent window was between 18% and 20%,

lenders have become more aggressive in obtaining a greater portion of the money owed them *before* the borrower reaches bankruptcy proceedings. For instance, credit card companies are believed to keep careful track of borrowers in danger of declaring bankruptcy; before the loans are discharged in court, these lenders wage a campaign of telephone calls and letter writing demanding partial payment.

Another reason may be that late fees may have risen for unsecured loans, lowering the costs associated with default and impending default. For example, though interest rates on credit cards have gone up 300% during the 1990s, now 20% of profits come from fees (Sullivan et al (2000) and Manning (2000)). If these efforts were broadly based across unsecured loans, costs of default would fall, and the result should be, then, that the default premium should fall. Since we see the premium increase for credit card loans, it may be that there are countervailing effects in this market. Perhaps, the need to price risk carefully prevails for credit card loans, and the counteracting effects dominate for the other unsecured loans.

Note that these premium spreads would not necessarily be observed if we instead looked at the actual population of those using certain types of loan pre- and post-1995. Here, the spreads are calculated using fixed risk classes – essentially giving us a way to summarize the coefficients on default risk in useful economic terms. We could also look at spreads for the population's actual borrowing in each time period, but this makes changes in pricing practices harder to isolate.[24,25]

B. **Interest Rate Estimation in Selection Models**

Here, I discuss the contributions of the other explanatory variables to interest rates in the base model. For first mortgages, the loan amount is insignificant, though the sign of the coefficient is negative, as predicted by the model. In addition, there is a small effect from home

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and only 25% of interest rates fell in this window. Without using 1983, we are left with 1995 and 1998 data. The premium in 1995 is 0.70, and it significantly rises in 1998 to 1.24.

[24] While mortgage refinancing was common post-1995 as interest rates fell, this should not falsely produce results of an increase in risk-based pricing. The data is constructed so that borrowers are only compared if their loans were originated in the same year. The default risk premium spread will not increase solely because some loans are a result of refinancing. On the other hand, refinancing booms may mean that older loans are more heavily weighted to those who received bad shocks and would not qualify for new low rates. While this may lead to a lower raw dispersion in interest rates pre-1995 (i.e. if old loans are *only* held by high-risk households), it will not lead to less dispersion *as a function* of risk.

[25] The increase in the mortgage rate default risk premium spreads is not simply due to the addition of a subprime market such that there is little spread within the prime and subprime markets. Rather than a bimodal distribution that this would give rise to, we continue to see a rather smooth bell-shaped distribution of mortgage interest rates post-1995. For example, 50% of the borrowers have rates between 7% and 8.5%, 20% are between 6% and 7% and 20% are between 8% and 9%.

equity where an increase of $100,000 held by the borrower predicts a decrease in the interest rate of 0.009 percentage points.[26]

For second mortgages, with a $10,000 increase in the loan amount, the interest rate falls by 0.051. Equity is insignificant for second mortgages, perhaps reflecting the remote chance that these lenders would receive any proceeds from a foreclosure sale. In the case of automobile loans, a $1,000 increase in the loan decreases the interest rate by 0.013.

Moving on to unsecured loans, interest rates on general consumer loans are better predicted by current loan balances rather than original loan amounts. This may be due to the more informal nature of this loan category. For example, these loans may be renegotiated more often so that current balance is also highly relevant for the interest rate. An increase of $10,000 in the loan balance at the time of the survey predicts a decrease of 0.006 in the interest rate.

For credit card loans, a $1,000 increase in credit card balances predicts a 0.021 increase in the interest rate. Similarly, for education an increase in the loan amount of $10,000 increases the interest rate 0.146 percentage points. These are the only loans where interest rates and loan amounts are positively related. This anomaly is left for future exploration, but possibly is related to the dominant presence of asymmetric information in these markets such that as households borrow more they are considered more likely to default.

C. Selection equation results

While the motivation of this paper is largely to explain interest rate variation and not the loan portfolio itself, the selection equations do present some interesting results. For many of the loan types, the explanatory variables predict a loan's inclusion in a family's portfolio, just as one would expect.[27] Across all loan types except education loans, we see the usual life cycle effect (with some allowance for young households being liquidity constrained as a result of no credit history) with the presence of loans increasing at first with age, then eventually decreasing as the household ages. The inclusion of education loans in the household portfolio decreases with age, as these loans will be more often taken out exclusively when young.

Interestingly, an increase in education generally signals less of a probability of having the various loan types (except first mortgages and education loans). This may be due to higher

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[26] A number of mortgage characteristics are not considered here. The inclusion of maturity, fixed versus flexible interest rates or FHA loan guarantees does not significantly alter the basic default risk premium spread results, and were excluded to simplify the empirical results and discussion.

[27] This preliminary discussion does not go into detail as to why these variables should be important from the lender's point of view beyond the polynomials for predicted bankruptcy and predicted late payments.

education households either paying off debt sooner when resources are available – recognizing that debt is costly – or simply choosing to forgo debt and use savings more often. In other words, higher education households may have lower reservation interest rates.

The natural log of income is significant for two secured loans with a positive sign and two unsecured loans with a negative sign. Intuitively, households with greater resources need to borrow less in high interest unsecured markets. In all cases where being married and number of kids are significant, their signs are positive. Being married and having children may be a sign of stability to a lender, increasing the chance that a loan is offered. On the other hand, being married may decrease the cost of a high interest rate since there is the potential for two incomes (i.e. a non-working spouse can choose to work,) in cases of bad times or unemployment. In other words, the cost of making loan payments in bad financial times may be lower. Having children should increase a family's desire for a loan – and thus increase the reservation interest rate – since a household's consumption needs increase.

A higher net worth reduces the probability that a household holds a particular loan probably resulting from the higher cost of external versus internal funds. However, higher assets partially counteract this effect. Certainly, lenders may look on high asset households more favorably when choosing whether to offer a loan, but another simpler reason for this effect is due to the timing of the data – households may buy assets with money from loans. In general, not having a checking account has a negative coefficient reflecting a lender's concern that a household does not have a stable financial situation and possibly a household's high cost of requesting a loan due to less familiarity with the financial system.

When the race indicator is significant for unsecured loans, its sign is positive. While the evidence shows that Black households are more likely to hold this higher interest debt, they are also less likely to hold first mortgages. Certainly, the race indicator may be a proxy for data not included in the SCF, or preferences may be playing a role. Black households may have higher reservation interest rates. In any case, this issue is left to further research.

The polynomials of unconditional bankruptcy risk have varying signs due to the complex nature of how, first, a lender will not offer a loan to a household that is *too* risky, and, second, a household will have a higher default risk when it has more loans. Finally, the attitudinal variables nearly always have positive coefficients when significant (except borrowing for a cut in income, which may be a sign of being fiscally conservative) , and the coefficient on the indicator variable for a household feeling that borrowing is a good thing is higher than that for a household feeling borrowing is only okay.

As predicted, when ρ is significant, it is negative, except for first mortgages. In general, when a household receives a lower than predicted interest rate, given its financial and demographic characteristics, it is more likely to include the loan in its financial portfolio.

VII. Implications for Borrowing

If lenders declined to charge very high-risk households sufficiently high interest rates prior to the increased use of default risk-based pricing, lending to this group may have proved unprofitable. As Bostic points out, without risk-based pricing, very high-risk people may have been rationed out of the market, rather than be charged high premiums (Bostic, (2002)). With the change in pricing, these very high-risk borrowers should be assessed suitable premiums rather than be denied. Indeed, Yezer states that even lenders who once dealt exclusively with low-risk groups will lend to a much broader range of borrowers with risk-based pricing (Yezer, (2002)). If the offered interest rates are not above the potential borrower's reservation interest rate, we should see use of the various types of consumer debt increase among very high-risk households.

To some extent, this effect is evident in the raw data. While the average income of survey respondents went up \$6,800 pre-1995 versus post-1995, the average income of those with debt went up only \$5,600 over the same time periods. Similarly, average education went up about one-half year overall, while the education of those with debt holdings went up a little over one-third year.

Changes in borrowing levels should also have occurred. Prior to the expanded use of risk-based pricing in the mid-1990s, low-risk borrowers were essentially paying relatively higher rates than were appropriate, and high-risk borrowers were paying lower rates. As premiums adjusted to better reflect risk, the spread between premiums for higher risk people and lower risk people increased. Reacting to changing interest rates, borrowing levels among low-risk households should have increased more (or decreased less) than levels for high-risk households.[28]

Encompassing the debt level and the access to debt effects, the following selection model is estimated using maximum likelihood:

[28] The change in the overall level of interest rates over time for a particular loan type will have its own effect. For example, interest rates fell across all risk classes for credit card loans, and all risk classes increased their credit card

$$\ln(\hat{B}_j) = \gamma^0 + \gamma^1 oyears_{95} + \sum_{i=1}^{3} \gamma^2{}_i \left(f_c(z_j, \theta_m) \right)^i + \sum_{i=1}^{3} \gamma^3{}_i oyears_{95} \left(f_c(z_j, \theta_m) \right)^i$$

$$\Pr(B_j > 1) = \Phi \left(\begin{array}{l} \beta^0 + \beta^1 years_{95} + \sum_{i=1}^{3} \beta^2{}_i \left(f_{uc}(z_j, \theta_m) \right)^i + \\ \sum_{i=1}^{3} \beta^3{}_i years_{95} \left(f_{uc}(z_j, \theta_m) \right)^i + \theta borrowing\ attitudes \end{array} \right)$$

Where B is the borrowing dollar level for the various consumer loan types. The year variables are year dummies accounting for changes in the cost of funds. *Oyear* is the loan origination year and *year* is the survey year. The third degree polynomial in bankruptcy risk accounts for possibility that consumer debt use varies with default risk, and the interaction terms measure how this use has changed across risk classes over time.

The results for both the access to debt and debt levels are shown in Figure 2 with 90% confidence bands. In the first row, the picture is quite clear for first mortgages. The highest-risk households have a higher probability of holding a first mortgage post-1995 versus pre-1995. Additionally, low-risk households are predicted to borrow more post-1995, consistent with a reaction to lower interest rates. The effect lessens as riskiness increases. Changes in interest rates also affect predictions of who holds debt. As interest rates fall for low-risk households, perhaps falling below reservation rates, these families have a higher probability of holding first mortgages. Conversely, as interest rates rise for high-risk groups, these households have a lower probability of holding this debt.

For automobile loans and credit cards loans, the picture for access to debt is similar to that for first mortgages. While the confidence intervals suggest less certainty for these loan types for very high-risk households, at least for credit card loans the post-1995 point estimates fall outside the range of the pre-1995 90% confidence bands. The predicted debt levels for automobile loans are quite consistent with the hypothesis. Indeed, we see that as a function of bankruptcy risk, conditional on holding debt, high-risk households are predicted to hold lower levels of automobile debt post-1995. Given that credit card debt became so much more popular through the 1990s, all credit card borrowers are predicted to increase debt levels.

Equivalent figures for the other debt types are less informative. Second mortgages are unique in that only households with first mortgages hold them, so access to this market is not as

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borrowing. However, they fell more for low-risk borrowers. In this case, we would expect borrowing to increase more for low-risk households than high-risk households.

a useful a question. Other consumer loans showed no significant increase in the premium spread, so there is little reason for the hypothesis to hold here. And finally, education loans show borrowing probabilities increasing over time across all risk classes, suggesting other exogenous effects are at work in this market.

Several aggregate debt categories are considered: all debt, all debt less mortgages and secured debt. All debt less mortgages is considered in order to ensure that results are not being driven simply by rising real estate prices making home ownership more attractive. All three aggregates bear out the hypothesis. Very high-risk households have a higher probability of holding debt, post-1995. Low-risk borrowers increase debt more than high-risk borrowers, and in some cases very high-risk borrowers actually decrease borrowing levels. Finally, consistent with interest rates falling below or rising above reservation rates, low-risk (high-risk) households have a higher (lower) probability of holding debt.

VIII. Actual and Predicted Increases in Debt Levels and Access to Debt Markets

That debt levels and the use of debt instruments increased in the 1990s has been the subject of much popular discussion using both data and anecdotal evidence. How much of these changes, pre-1995 to post-1995, can risk-based pricing explain? Answering this question necessitates estimating borrowing levels and use of debt allowing for risk-based pricing but no other changes over this period. Essentially, I need to exclude any economy-wide level effects such as changes in the cost of funds for lenders or general changes in laws and attitudes.

For this analysis, I will need to use default risk quantiles rather than smooth measures of risk. Many households have essentially zero default risk. To estimate the reaction to risk-based pricing for these very low-risk households, I need to represent them by some measure other than zero. Otherwise, any possibly changing coefficient for this risk group, pre- versus post-1995, will be rendered ineffective. The preceding section shows that the borrowing levels of these low-risk groups reacted strongly to the increased use of risk-based pricing. Using quantile dummies, I can get different effects before and after 1995 for households with zero default risk. The preceding section's results regarding use of borrowing instruments and debt levels informs the decision for which risk group is restricted to no change in order to identify the model. Robustness checks shows that the choices are quite reasonable.

The following model is estimated for the various types of consumer debt, where B_j is the borrowing level for household j:

$$\ln(\hat{B}_j) = \gamma^0 + \gamma^1 oyears_{95} + \sum_{i=1}^{4} \gamma^2{}_i \times (risk\,class = i\,of\,5) + \sum_{i=1}^{4} \gamma^3{}_i oyears_{95} \times (risk\,class = i\,of\,5)$$

$$\Pr(B_j > 1) = \Phi\left(\begin{array}{l} \beta^0 + \beta^1 years_{95} + \sum_{i=2}^{10} \beta^2{}_i \times (risk\,class = i\,of\,10) + \\ \sum_{i=2}^{10} \beta^3{}_i years_{95} (risk\,class = i\,of\,10) + \theta borrowing\,attitudes \end{array}\right)$$

For the probit, more risk quantiles are used since some of the most interesting changes for the use of borrowing instruments occur for the very high-risk groups. In fact, the tenth quantile is further divided into four finer divisions of risk. The risk classes for the borrowing levels use conditional bankruptcy risk, and the classes for the probit use unconditional bankruptcy risk.

Figure 3 plots the changes for borrowing levels and use of the debt instrument for first mortgages, automobile loans and all debt. Probabilities of holding debt are shown as a function of unconditional bankruptcy risk. In contrast, debt levels are shown as a function of conditional bankruptcy risk quantiles. The levels plots are easier to read with simple data points since nearly all the changes take place for households in the first quantile. Since there is nearly zero variation in bankruptcy risk for these households – they are all clustered at zero – smooth plots are difficult to read. 90% confidence intervals are shown.[29]

Figure 3 also allows us to ask how much in aggregate the model predicts for borrowing levels and use of debt given the changes to loan pricing that occurred in the mid-1990s. These numbers can be compared to the actual changes that took place over this time period. In all, the model predicts anywhere from about 25% to 75% of the actual increases in average debt levels. For example, the model predicts that risk-based pricing would have added over $7,000 to the average mortgage amount excluding any economy-wide changes. In the data, actual mortgages originated after 1995 versus those originated before 1995 increased about $30,000. Similarly for automobile loans, the model predicts an increase of nearly $1,500 in the average loan size, whereas actual automobile loans increased over $2,000. The average debt burden for households holding debt went up about $14,000 over the mid-1990s. The model predicts an increase of nearly $6,000.

[29] These confidence intervals reflect the prediction error in the betas without the additional error associated with the residual. These plots do not represent genuine forecasts of levels and use of debt, only the levels and use predicted by risk-based pricing which is summarized by the coefficients. However, including the error associated with the residual generally makes both sets of confidence intervals so large as to include pre- and post-1995 point estimates.

In contrast, the model over-predicts the increased use of various debt instruments. For first mortgages, there was an actual increase of 3 percentage points of the population holding mortgages from before 1995 to after 1995 in the survey data. The model predicts an increase of nearly 8 percentage points. The percentage of households holding automobiles loans went up only 0.06 point, whereas the model predicts an increase of 0.5 point. The highest risk group had much larger changes. In the data, the percentage holding automobile loans went up 2.6 points, and the model predicts an increase of 3.2 percentage points. For all debt, there was an increase of 2.2 percentage points in the number of families holding any form of debt, and the model predicts an increase of almost 7 points.

Figure 3 is meant to be only illustrative of how well risk-based pricing may explain aggregate changes in debt markets over the 1990s. Other changes that were similarly heterogeneous across risk-classes could also account for the models predictions. For example, if attitudes towards risk changed in the same manner that risk-based pricing affected various risk groups – if only the lowest risk groups became exogenously more amenable to high debt levels over the time period – such changes could not be rejected as alternative reasons for the predictions.

IX. Model of Interest Rate Determination

A simple theoretical model of interest rate determination is useful is assessing the reasonableness of the default risk premium spreads found in section VI. Additionally, this model will give an idea of whether interest rates have fully adjusted to the increased use of default risk-based pricing. In this partial-equilibrium model, interest rates will result from the lender's evaluation of the loan's profit-making potential. I assume that the lenders behave as if risk neutral, so that they must only ensure non-negative economic profits in expectation. To see risk neutral behavior, one can posit that either the lender is risk neutral or that the lender is able to diversify risk well enough to recover *ex post* the normal rate of return on an entire portfolio of loans. Competition drives economic profits to zero.[30]

To make things concrete, let us conjecture that an agent approaches a lender with an application for a given loan, is offered an interest rate, and then chooses whether to take the loan,

[30] While there are not extensive recent studies of the extent of competition in consumer loan markets, older studies largely concluded that these markets were relatively competitive. Surely, competition has only intensified in recent years (Durkin and Elliehausen, (2002)).

not to take the loan, or to request a loan with different terms. The agent's decision to request the loan is beyond the scope of this simple model (as is the source of loanable funds), which only pins down the interest rate offered by the lender.

As in Hester's model of the loan offer function, interest rates vary with the size of the loan, the extent of loan recovery in default, maturity, fixed costs of issuance, the lender's discount rate, and, of course, default risk (Hester, (1967)). In addition, the loan is constructed so that the borrower must make constant payments over the life of the loan. First, I introduce some notation:

T = maturity of loan or time frame over which default risk is assessed, whichever is shorter

i = gross interest rate charged

o = the lender's discount rate. It is the required rate of return to cover the cost of capital (i.e. loanable funds), or in other words, the required return to shareholders.

d = uniform probability of default in all periods

l = fraction of loan recovered on default including transaction costs, c, of foreclosure. If there is collateral, l is a function of equity in collateral. Even if there is no collateral, l is unlikely to be 0 since a lender does have some recourse such as garnishing wages or collecting from non-exempt assets sold depending on the nature of default. For our immediate purposes, l is taken as a constant for a given type of loan, but an interesting extension of this model would be to model l as a function of collateral equity.

f = fixed costs of issuing each loan

A = amount of the loan

In brief, the expected net present value of the payments over the life of the loan must equal zero given the lender's discount rate o. The result is the following:

$$A - f = \sum_{t=1}^{T} \frac{1}{o^t}[X(1-d)^t + l(A - \sum_{s=0}^{t-1} P_s) \; d(1-d)^{t-1} \; i]$$

$$where \quad X \equiv \frac{A}{\sum_{t=1}^{T} \frac{1}{i^t}}$$

$$and \qquad P_t \equiv X - (A - \sum_{s=1}^{t} P_{s-1})(i-1) \; ; \; P_0 = 0$$

Note that X is the constant payment (including principal and interest) made over the life of the loan, and P_t is the total principal paid at date t.

This model makes several intuitive predictions about interest rates as a function of loan attributes. Figure 4 shows how the interest rate varies with the parameters of the model. Interest rates are linear in the discount rate, the fraction of loan recovery in default and in the fixed costs. Due to fixed costs and linear pricing, interest rates fall at a decreasing rate with increases in the loan amount. (With no fixed costs, interest rates do not vary with loan size.) Interest rates also fall with increases in maturity, also at a decreasing rate. Though a borrower's overall probability of default increases with maturity, a lender also has more time over which to make the required return. Finally, and most important for the empirical work, interest rates increase with default risk, at a slightly increasing rate though it is nearly linear. While the levels and slopes of the curves are dependent in part on the parameters chosen, the overall relationships are robust to other reasonable parameter specifications.

Note that as in the empirical work, simplifying assumptions are made with regards to default risk. Default risk is set to a constant uniform rate over the life of the loan. In reality, the lender would want to incorporate a possibly changing level of default risk over the course of the loan. For example, a mortgage lender may predict that a borrower's level of default risk will fall as the borrower should become more financially experienced and better educated in the future. These predictions of borrower attributes will be subject to the usual forecast error, leading to uncertainty regarding future default risk. For now, these complications are ignored, and a simple uniform d is used.

X. Reconciling Empirical Results with Theory

The model of interest rate determination discussed in section IX can be used to estimate theoretical risk premiums. First, it is necessary to identify reasonable parameters values as inputs into the model. To review, the model requires values for o, A, l, f, T and d. The risk premium is the difference in interest rates for two default risks, d. These two *d's* are calibrated from the empirical work in the section *Evidence of Changing Default Risk Premium,* namely the two year default risk as $d=0.02$ and $d=0.00$.

Loan maturities are taken from the loan data. For first mortgages, $T=30$, as nearly 60% of first mortgages have 30 year maturities. Similarly, for second mortgages, $T=10$, as this matches nearly 30% as these loans. Automobile loans have $T=5$, corresponding with almost 35% of the loans. $T=1$ for general consumer loans, reflecting the maturity of almost 25% of these loans.

Finding the average maturity of credit card loans is less straightforward, because this data is unavailable. For these loans, T is approximated at 1 year. Education maturity period is most often 10 years; so for these loans, $T=10$.

Presumably, the interest rate equation coefficients should give estimates of fixed costs for each loan type. Unfortunately, the empirical models suggest implausibly low fixed costs.[31] In reality, lenders are probably recovering at least some of the fixed costs through points in the case of mortgages and fees for the other types of loans. Data on fixed costs from the consumer credit industry will serve the purpose.

Public balance sheets from consumer banks suggest that administrative costs are over \$1,500 for first mortgages and \$240 for automobile loans. The American Bankers Association publishes reports on expenses associated with loans backed by home equity and installment loans. According to their surveys, the median cost associated with all home equity loans is \$372 (ABA Home Equity Lending Survey Report, 2002)). Of course, this will include many smaller and less complicated loans than first mortgages. Costs for installments loans are on average between \$106 and \$141 per loan depending on the nature of the loan (ABA Installment Credit Survey Report, 2002)). Using some judgment given this data, the following costs per loan are assumed: first mortgages, \$1000; second mortgages, \$350, automobile loans, \$240; general consumer loans and credit card loans, \$105; and education loans, \$140.

Values for l are taken from research on the credit industry; for first mortgages, $l=0.68$. In bankruptcy, the average value of the collateral on mortgages is 97% of the loan. In foreclosure, bankruptcy courts demand due diligence from lenders in selling real estate, and generally set a floor of 70% of market value for the selling price. Not surprisingly, lenders argue this floor is too high (Sullivan et al, (1989)). If 70% is reasonable, this leads to a value of $l=0.68$. Evidence in favor of an l this high comes from a lending executive quoted in the *New York Times* who estimated that Fannie Mae and Freddie Mac lose \$12,000 on typical a foreclosure (Leonhardt (2002)). Given that the recent median first mortgage for those with late mortgage payments is \$54,000, this suggests a recovery ratio of 0.77. On the whole, $l=0.68$ is a conservative estimate.

Less is known regarding the recovery rate of second mortgages in default. Certainly, if first mortgage lenders have deficiencies after foreclosure, there is clearly nothing left for second mortgage issuers. So, l should be significantly less than 0.68. A 1998 bankruptcy study by the

[31] Linearity was used because it worked well for realistically narrow parameter values. Backing out fixed costs from the coefficients requires imputing unrealistic parameters values such as $d=0$.

Wharton Econometric Forecasting Associates (WEFA) figured an average 5% recovery for unsecured and 40% for secured debt in bankruptcy (Luckett, (2002)). For second mortgages, l is thus taken to be 0.4.

In bankruptcy, the market value of automobiles is worth approximately 70% of the loan amount (Sullivan et al, (1989)). Using the same floor for lenders selling repossessed vehicles of 70% of market value, lenders should recover an average of 50% of loan in default. However, 70% of market value is probably too high for this market, given selling costs and the anecdotal evidence on selling repossessed cars. 50% of market value leads to an l of 0.35. Given the WEFA study, $l=0.4$ is taken as a safe compromise.

The WEFA study also discusses recovery rates for unsecured debt. While these lenders often claim to receive nothing in bankruptcy court, $l=0.05$ is a more realistic estimate for general consumer and credit card loans. Education loans should have a higher recovery rate, however, because they are usually not dischargable in bankruptcy court. As a compromise, $l=0.2$ is assumed for education loans reflecting that these are something of a mix between secured and unsecured loans.

Discount rates, o, are taken from the interest rate data, calculated by the average rate for the 10% least risky for each loan type, for loans originated in 1998. Loan amounts, A, are taken from median values, again for origination year 1998.

The results are shown in Table 14. As expected, premiums are higher for non-collateralized loans versus collateralized loans. In addition, while the premiums do not correspond to the empirical results exactly (shown in Table 10), they are certainly the right order of magnitude. One important issue remains unresolved. First, the risk premiums in Table 14 for secured loans more closely match the empirical pre-1995 premiums, rather than the presumably more precise post-1995 premiums. Only for the empirical unsecured loans premium does post-1995 seem to be closer to the theoretical premium.

One possibility is that the parameter values are inappropriate. Table 15 shows alternative choices for l and f that achieve theoretical premiums closer to the post-1995 empirical premiums. What is immediately apparent is that even dramatic changes in the costs of issuing loans have little effect on the risk premiums. Additionally, matching post-1995 empirical premiums is difficult using reasonable parameter values. As an example, even with a zero recovery rate, the automobile premium is only 1.11, nearly 1.4 percentage points lower than the post-1995 empirical premium of 2.50 in Table 10. While this issue is unresolved, it certainly implies that we are not likely to see even *greater* increases in the spreads as a result of changes in pricing practices. The theoretical model suggests that interest rates have fully adjusted to the increased use of default risk- based pricing.

XI. Conclusion

Overall, economists have much less of an understanding of the household's borrowing instruments than saving instruments. Extensive research has been done on how households choose savings portfolios, how returns on those portfolios are determined, and, in turn, what impact the portfolio returns have on the household. In contrast, much less is known about the borrowing portfolio even though roughly 70% of households hold debt. Indeed, even less is understood about borrowing interest rates specifically, despite their importance in household decision-making. In a national survey of borrowers, the interest rate ranked the most important factor in considering whether to accept a loan contract from a lender (Durkin and Elliehausen, (2002)).

This paper's goal is to increase our understanding of how consumer loan markets function by examining whether consumer lenders changed their interest rate pricing practices in the mid-1990s, more aggressively using risk-based pricing. In the process, I estimate the extent of default risk's role in interest rate setting by using two sources of risk: the risk of being late on payments and the risk of bankruptcy. Both contribute to the determination of interest rates from 1983 to 1998.

I show that the risk premiums for collateralized loans (first and second mortgages and automobile loans) have clearly gone up over time, at least nearly doubling in all cases. The case for non-collateralized loans is less clear. The premium for credit card loans does indeed more than double, but education loan premiums are statistically unchanged, while general consumer loan premium actually fall a slight amount (though not significantly). Finally, while other explanations cannot be entirely rejected, I present evidence that variations over time in household's level of debt and use of debt instruments are consistent with this change in pricing practices.

Given the effects that risk-based pricing appears to have on debt levels and access to debt, there should be important welfare implications. While very high-risk and low-risk households have benefited from these changes, high-risk households have seen their premiums increase and have changed their borrowing in response. The welfare implications are the subject of future work and are a natural extension of this analysis.

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XIII. Appendix Corrected Standard Errors

Because $f\left(z,\hat{\theta}_m\right)$ and $g\left(d,\hat{\theta}_M\right)$ are generated regressors with their own associated standard errors, the standard errors on the $\gamma's$ must be adjusted. The adjustment follows Murphy and Topel (1985). Using the notation defined in the preceding sections, the corrected variance-covariance matrix is as follows:

$$\Sigma = -E\left[\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\gamma}\partial\hat{\gamma}'}\right]^{-1} - E\left[\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\gamma}\partial\hat{\gamma}'}\right]^{-1} E\left[\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\theta}\partial\hat{\gamma}'}\right]' E\left[\frac{\partial^2 L_1(\hat{\gamma};\hat{\theta})}{\partial\hat{\theta}\partial\hat{\theta}'}\right]^{-1} E\left[\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\theta}\partial\hat{\gamma}'}\right] E\left[\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\gamma}\partial\hat{\gamma}'}\right]^{-1}$$

Where

$$-E\left[\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\gamma}\partial\hat{\gamma}'}\right]^{-1}$$

is the uncorrected variance-covariance matrix from the interest rate selection model. From the estimation of bankruptcy and delinquency risk:

$$E\left[\frac{\partial^2 L_1(\hat{\gamma};\hat{\theta})}{\partial\hat{\theta}\partial\hat{\theta}'}\right]^{-1}$$

where L_1 is the stacked likelihood function from these first step probits, and θ is a $(m+M\times 1)$ vector of stacked probit parameters θ_m and θ_M. What remains is the rather messy uncovering of the matrix

$$E\left[\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\theta}\partial\hat{\gamma}'}\right].$$

The log-likelihood contribution of individual *i* in the selection model is as follows:

$$l_j = \begin{cases} \ln\Phi\left(\dfrac{H_j\beta + \left(y_j - \mathrm{X}_j\gamma\right)\dfrac{\rho}{\sigma}}{\sqrt{1-\rho^2}}\right) - \dfrac{1}{2}\left(\dfrac{y_j - \mathrm{X}_j\gamma}{\sigma}\right)^2 \; y_j \; observed \\ \ln\Phi\left(-H_j\beta\right) \; y_j \; unobserved \end{cases}$$

The cross-derivative matrix is recovered from the following equations:

y_j *observed* :

$$\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\theta}\partial\hat{\gamma}'} = f_\theta^j\left[S_{1\_b}S_2\left(\frac{\partial(\mathrm{X};\gamma)}{\partial C'}-\frac{\sigma}{\rho}\frac{\partial(H;\beta)}{\partial C'}\right)+f_c\left(\frac{y_j-\mathrm{X}_j\gamma}{\sigma^2}-S_3\right)+\frac{\sigma}{\rho}S_3B_{fc}-\left(\frac{I_{95}\gamma_{k-3}+\gamma_{k-2}}{\sigma^2}\right)\frac{\partial(\mathrm{X};\gamma)}{\partial C'}\right]+$$

$$g_\theta^j\left[S_{1\_l}S_2\left(\frac{\partial(\mathrm{X};\gamma)}{\partial C'}-\frac{\sigma}{\rho}\frac{\partial(H;\beta)}{\partial C'}\right)+g_c\left(\frac{y_j-\mathrm{X}_j\gamma}{\sigma^2}-S_3\right)+\frac{\sigma}{\rho}S_3B_{gc}-\left(\frac{I_{95}\gamma_{k-1}+\gamma_k}{\sigma^2}\right)\frac{\partial(\mathrm{X};\gamma)}{\partial C'}\right]$$

y_j *unobserved* :

$$\frac{\partial^2 L_2(\hat{\gamma};\hat{\theta})}{\partial\hat{\theta}\partial\hat{\gamma}'} = -f_\theta^j\left[S_5B_{fc}+S_4\frac{\partial(H;\beta)}{\partial C'}\left(\beta_{l-3}+2f_j\beta_{l-2}\right)\right]-g_\theta^j\left[S_5B_{gc}+S_4\frac{\partial(H;\beta)}{\partial C'}\left(\beta_{l-1}+2g_j\beta_l\right)\right]$$

where

$$S_j = \frac{H_j\beta+\left(y_j-\mathrm{X}_j\gamma\right)\frac{\rho}{\sigma}}{\sqrt{1-\rho^2}}$$

$$S_{1\_b} = \frac{\beta_{l-3}+2f_j\beta_{l-2}-\frac{\rho}{\sigma}\left(I_{95}\gamma_{k-3}+\gamma_{k-2}\right)}{\sqrt{1-\rho^2}}$$

$$S_{1\_l} = \frac{\beta_{l-1}+2g_j\beta_l-\frac{\rho}{\sigma}\left(I_{95}\gamma_{k-1}+\gamma_k\right)}{\sqrt{1-\rho^2}}$$

$$S_2 = \frac{\rho\left(S_j\phi(S_j)\Phi(S_j)+\phi(S_j)^2\right)}{\Phi(S_j)^2\sigma\sqrt{1-\rho^2}}$$

$$S_3 = \frac{\rho\phi(S_j)}{\Phi(S_j)\sigma\sqrt{1-\rho^2}}$$

$$S_4 = \frac{-H_j\beta\phi(-H_j\beta)\Phi(-H_j\beta)+\phi(-H_j\beta)^2}{\Phi(-H_j\beta)^2}$$

$$S_5 = \frac{\phi(-H_j\beta)}{\Phi(-H_j\beta)}$$

XIV. Tables and Figures

Table 1. Interest Rate Data for loans originated in 1998

	Mean Interest Rate	*Standard Deviation*	*Observations across all origination years*
1st Mortgage Rate	7.75%	1.53	8,143
2nd Mortgage Rate	10.57	2.63	805
Auto Loan Rate	9.92	4.53	5,209
Credit Card Rate	14.45	5.01	4,007
Other Consumer Loan Rate	13.28	6.69	2,744
Education Loan Rate	8.35	1.96	997

Table 2. ***Attitudinal variables vs. debt***

	1st Mortgage 38%**	2nd Mortgage 4%	Auto Loan 30%	Any line of credit 3%	Other Consumer 22%	Credit Card 39%	Education Loan 4%	Any debt 72%
Borrowing is generally good – 40%*	38%	4%	34%	3%	23%	30%	3%	77%
Borrowing is generally okay – 31%	39	5	29	3	18	29	4	73
Borrowing is ok for...vacation – 14%	39	5	33	5	25	37	5	81
...a cut in income – 45%	35	4	28	3	21	26	4	73
...to buy furs and jewelry – 5%	45	5	37	5	21	39	6	84
...to buy a car – 81%	42	5	34	3	21	29	4	78
...for education expenses – 80%	40	4	32	3	21	28	4	76

*Frequencies reported are the percentage of all the households who responded "yes" for the attitudinal variables that also hold the relevant form of debt. * these are the percentages of those responding "yes" in the total population ** percentage of households holding each kind of debt.*

Table 3. Declaration of Bankruptcy, Conditional Probability

	Coefficient	Robust Standard Error	p-value	$\partial(probability)/\partial x$
1989*	0.319	0.174	0.067	0.0051
1994*	0.470	0.156	0.003	0.0068
Age	0.011	0.020	0.588	1.38E-04
Age squared	-2.49E-04	2.27E-04	0.272	-3.25E-06
No checking account*	0.305	0.091	0.001	0.0052
Ln(Income)	0.056	0.032	0.080	0.0007
Self employed*	0.287	0.126	0.022	0.0051
Home Ownership*	0.302	0.176	0.087	0.0035
Home Ownership x 1989*	-0.210	0.218	0.335	-0.0023
Home Ownership x 1994*	-0.405	0.199	0.041	-0.0045
NC Debt/Income>2*	0.328	0.261	0.209	0.0066
Positive Net worth	-3.35E-06	1.07E-06	0.002	-4.37E-08
Non-collateralized Debt	1.70E-06	8.98E-07	0.058	2.22E-08
Unemployed*	-0.309	0.230	0.180	-0.0028
Black*	-0.110	0.091	0.227	-0.0013
Education Class	-0.105	0.041	0.011	-0.0014
Single Parent*	0.165	0.101	0.103	0.0026
Constant	-2.892	0.516	0.000	

(*) d(probability)/dx is for discrete change of dummy variable from 0 to 1

Table 4. Declaration of Bankruptcy, Unconditional Probability

	Coefficient	Robust Standard Error	p-value	$\partial(probability)/\partial x$
1989*	0.328	0.110	0.003	0.0037
1994*	0.368	0.095	0.000	0.0034
Age	0.017	0.015	0.253	1.49E-04
Age squared	-3.06E-04	1.69E-04	0.071	-2.68E-06
No checking account*	0.252	0.083	0.002	0.0026
Ln(Income)	0.082	0.033	0.015	0.0007
Self employed*	0.228	0.110	0.038	0.0026
Assets*	-8.02E-07	4.38E-07	0.067	-7.01E-09
Assets x 1989*	-9.60E-07	8.03E-07	0.232	-8.39E-09
Assets x 1994*	-1.74E-06	7.36E-07	0.018	-1.52E-08
Unemployed*	-0.307	0.174	0.077	-0.0019
Black*	-0.158	0.080	0.048	-0.0013
Education Class	-0.018	0.038	0.633	-0.0002
Single Parent*	0.079	0.086	0.359	0.0007
Constant	-3.461	0.449	0.000	

(*) d(probability)/dx is for discrete change of dummy variable from 0 to 1

Table 5. Predicted bankruptcy rates (in fractions) within two years of survey date

	Conditional Estimates		Unconditional Estimates	
	PSID	SCF	PSID	SCF
Percentiles: 1%	0.0000	0.0000	0.0000	0.0000
10%	0.0002	0.0001	0.0001	0.0001
25%	0.0019	0.0012	0.0021	0.0013
50%	0.0067	0.0058	0.0061	0.0049
75%	0.0143	0.0134	0.0117	0.0113
90%	0.0216	0.0228	0.0179	0.0174
99%	0.0514	0.0531	0.0340	0.0330
Range	0.00 – 0.24	0.00 - 0.86	0.00 – 0.059	0.00 – 0.99
Mean	0.0099	0.0091	0.0080	0.0073
Standard Deviation	0.0116	0.0145	0.0077	0.0077

Table 6. Household Characteristics by Conditional Bankruptcy Probability Quantile

	1st Quantile	2nd Quantile	3rd Quantile	4th Quantile	5th Quantile	Overall Average
Bankruptcy Probability	0.0%	0.2%	0.6%	1.2%	2.8%	0.9%
Age	55.48	51.18	43.72	37.84	33.54	44.35
No Checking Account*	0.028	0.026	0.067	0.110	0.387	0.124
Income	$106,000	$48,800	$42,750	$37,620	$27,680	$52,580
Self Employed*	0.217	0.099	0.069	0.080	0.135	0.120
Home Ownership*	0.919	0.840	0.751	0.607	0.346	0.693
Non-collateralized Debt/Income>0.2*	0.039	0.006	0.005	0.003	0.044	0.019
Net Worth	$885,700	$141,000	$70,980	$34,100	$10,930	$228,600
Non-collateralized Debt	4,976	3,139	3,310	4,297	6,661	4,477
Unemployed*	0.068	0.091	0.073	0.047	0.056	0.067
Black*	0.063	0.115	0.128	0.134	0.141	0.116
Years of Education	14.41	13.38	13.13	13.00	11.83	13.15
Single Parent*	0.047	0.054	0.085	0.119	0.243	0.109

* Number reported is proportion of population.

Table 7. Late Payment Indicator

Probit Equation

	Coefficient	Robust Standard Error	p-value
1989	0.724	0.407	0.08
1992	-0.077	0.173	0.66
1995	-0.399	0.135	0.00
1998	-0.106	0.142	0.46
Age	0.026	0.009	0.00
Age squared	-4.47E-04	9.81E-05	0.00
No checking account	0.346	0.058	0.00
Ln(Income)	0.014	0.007	0.03
...x 1989	-0.121	0.039	0.00
...x 1992	-0.038	0.015	0.01
...x 1995	0.006	0.011	0.58
...x 1998	-0.025	0.012	0.04
Self employed	-0.032	0.094	0.73
...x 1989	0.198	0.161	0.22
...x 1992	0.285	0.145	0.05
...x 1995	0.047	0.153	0.76
...x 1998	0.247	0.153	0.11
Home Ownership	-0.097	0.072	0.18
...x 1989	-0.188	0.123	0.12
...x 1992	-0.229	0.112	0.04
...x 1995	-0.206	0.107	0.05
...x 1998	-0.059	0.113	0.60
NC Debt/Income>2.5	0.370	0.123	0.00
Positive Net worth	-7.00E-08	4.66E-08	0.13
...x 1989	6.18E-08	4.75E-08	0.19
...x 1992	7.41E-09	5.65E-08	0.90
...x 1995	-6.05E-08	9.11E-08	0.51
...x 1998	-5.85E-07	2.55E-07	0.02
Non-collateralized Debt	1.40E-07	1.10E-07	0.20
Unemployed	0.188	0.102	0.07
...x 1989	0.238	0.192	0.22
...x 1992	-0.533	0.216	0.01
...x 1995	-0.271	0.208	0.19
...x 1998	0.040	0.188	0.83
Black	0.484	0.086	0.00
...x 1989	-0.107	0.153	0.49
...x 1992	-0.259	0.155	0.10
...x 1995	-0.247	0.145	0.09
...x 1998	-0.183	0.136	0.18
Education Class	-0.091	0.016	0.00
Single Parent	0.122	0.053	0.02
Constant	-1.234	0.203	0.00

Selection Equation

1989	0.098	0.036	0.01
1992	0.083	0.034	0.02
1995	0.060	0.033	0.07
1998	0.067	0.033	0.04
Age	0.041	0.004	0.00
Age squared	-7.24E-04	4.17E-05	0.00
No checking account	-0.478	0.036	0.00
Ln(Income)	0.004	0.003	0.16
Self employed	-0.054	0.028	0.06
Home Ownership	0.629	0.028	0.00
Positive Net worth	-2.26E-09	6.34E-10	0.00
Unemployed	-0.335	0.042	0.00
Black	0.136	0.040	0.00
Education Class	0.036	0.009	0.00
Single Parent	0.068	0.040	0.09
borrowing is good	0.228	0.028	0.00
borrowing is okay	0.115	0.027	0.00
borrowing ok for vacation	0.147	0.035	0.00
for a cut in income	-0.035	0.023	0.13
for furs and jewelry	0.028	0.050	0.57
for a car	0.390	0.028	0.00
for education	-0.027	0.030	0.37
Constant	-0.281	0.113	0.01

Table 8. Predicted Probability of Late Payments (in fractions)

	SCF
Percentiles: 1%	0.001
10%	0.010
25%	0.026
50%	0.056
75%	0.118
90%	0.207
99%	0.479
Range	0.000 – 0.99
Mean	0.089
Standard Deviation	0.098

Table 9. Interest Rates Moments by Loan Origination Year and Risk Classes over Time

	1989 High Risk vs. Low-risk Spread†	*1995 High-risk vs. Low-risk Spread*†	*1998 High-risk vs. Low-risk Spread*†	*1989 standard deviation*	*1995 standard deviation*	*1998 standard deviation*
1st Mortgage Rate*	0.53	0.59	0.69	1.16	1.26	1.49††
2nd Mortgage	2.65	1.75	2.84	2.21	2.82††	2.63
Auto Loan	1.40	2.42††	3.94††	3.58	4.05††	4.53††
Credit Card **	-0.99	1.05††	1.22	4.18	4.43††	5.01††
Other Consumer Loan	0.08	3.03††	4.06	4.47	6.07††	6.69
Education Loan	-0.02	1.30	0.26	3.37	4.05††	1.96

* *To reduce raw variance in mortgage rates simply due to mortgage terms, only 30 year fixed rate mortgages are considered here.*

** *As credit card rates are not available for 1989, 1983 is used where the table indicates 1989.*

† *In order to have a reasonable number of observations, 1998 spreads are taken from years 1998 and 1997, 1995 spreads represent years 1995 and 1996, and 1989 spreads are computed for 1988 and 1987 (except for credit card rates which are computed for single years).*

†† *Difference between current and preceding year's number is significant with p-value<0.1.*

Table 10. Default Risk Premium Spreads

	Pre-1995 Risk Premium Spread	*Post-1995 Risk Premium Spread*
1st Mortgage Rate*	0.50	0.98
2nd Mortgage Rate*	0.98	3.97
Auto Loan Rate*	1.08	1.94
General Consumer Loan Rate	1.19	1.08
Credit Card Rate*	-0.53**	1.30
Education Loan Rate	0.03**	0.41**

** Difference is significant at a 95% confidence level. ** Spread is insignificantly different from zero.*

Table 11. Default Risk Premium Spreads from Alternative Models

	Base Model	Late Payments replaces $g\left(d,\hat{\theta}_M\right)$	I_{96} replaces I_{95}	No $f_c\left(z,\hat{\theta}_m\right)$	No $g\left(d,\hat{\theta}_M\right)$
Pre-1995					
1st Mortgage Rate	0.50	0.23	0.51	0.45	0.17
2nd Mortgage Rate	0.98	0.61	1.02	0.78	0.52*
Auto Loan Rate	1.08	0.99	1.19	0.63	0.99
General Consumer Loan Rate	1.19	0.35	1.18	1.23	0.16*
Credit Card Rate	-0.53*	-1.02	0.58	-0.30*	-1.11
Education Loan Rate	0.03*	0.01*	0.02*	0.11*	-0.02*
Post-1995					
1st Mortgage Rate	0.98	0.97	1.00	0.66	0.90
2nd Mortgage Rate	3.97	3.90	4.16	3.04	3.88
Auto Loan Rate	1.94	0.99d	2.12	1.90	0.77* d
General Consumer Loan Rate	1.08 d	0.05* d	1.23d	1.15 d	-0.01* d
Credit Card Rate	1.30	0.80	1.31	1.20	0.58
Education Loan Rate	0.41*d	0.66* d	0.56* d	0.69	0.54*d

All spreads and differences in spreads are statistically significant unless otherwise noted.
*Spread is insignificant.
d Difference in spreads is insignificant.

Table 12. Coefficients from Base Model and Alternative Models

	Base Model	Late Payments replaces P(Late Payments)	I_{96} replaces I_{95}	No P(bankruptcy)	No P(Late Payments)
1st mortgage rate coefficients					
Loan amount	-1.04e-7	-1.50e-7*	-1.11e-7	-1.04e-7	-1.51e-7*
Equity in home	-8.34e-8*	-1.33e-7*	-8.36e-8*	-8.48e-8*	-1.46e-7*
P(bankruptcy)	2.46	5.34*	2.68		6.14*
P(Late Payments)	4.34*	0.61*	4.38*	4.47*	
P(bankruptcy)*I_{95}	21.79*	26.49*	23.84*		26.55*
P(Late Payments)*I_{95}	-1.28	0.06	-1.74	2.17	
Constant	16.77*	8.82*	16.75*	16.73*	8.82*
2nd mortgage rate coefficients					
Loan amount	-2.19e-6*	-2.23e-6*	-2.21e-6*	-2.19e-6*	-2.32e-6*
Equity in home	6.47e-9	-7.20e-8	1.20e-8	-1.61e-8	-1.62e-7
P(bankruptcy)	8.66	15.66	9.59		18.67
P(Late Payments)	7.41*	1.28*	7.51*	7.81*	
P(bankruptcy)*I_{95}	100.22*	116.64*	112.48*		121.52*
P(Late Payments)*I_{95}	2.23	0.42	0.39	22.58*	
Constant	19.11*	10.53*	19.15*	18.99*	21.14*
Automobile rate coefficients					
Loan amount	-1.3e-5*	-1.91e-5*	-1.33e-5*	-1.42e-5*	-2.02e-5*
Equity in auto	2.48e-7	2.56e-7	2.92e-7	2.97e-7	2.54e-7
P(bankruptcy)	22.20*	34.64*	25.86*		35.90*
P(Late Payments)	4.65*	0.25	4.75*	6.32*	
P(bankruptcy)*I_{95}	-19.36	-9.23	-26.42*		-8.20
P(Late Payments)*I_{95}	13.99*	1.81*	16.61*	12.70*	
Constant	16.72*	17.74*	16.70*	16.48*	17.74*
General Consumer Loan coefficients					
Loan amount	-1.33e-7	-1.05e-7	-1.34e-7	-1.28e-7	-9.89e-8
Loan Balance	-5.88e-7*	-7.23e-7*	-5.81e-7*	-6.22e-7*	-7.72e-7*
P(bankruptcy)	-1.78	3.49	-1.93		5.95
P(Late Payments)	12.45*	1.81*	12.37*	12.38*	
P(bankruptcy)*I_{95}	-6.85	-3.41	-7.52*		-6.45
P(Late Payments)*I_{95}	0.75	-1.44	2.52	-0.86	
Constant	11.08*	14.48*	11.07*	11.03*	15.21*
Credit card loan coefficients					
Loan Balance	2.10e-5*	1.70e-5*	1.99e-5*	2.19e-5*	1.80e-5*
P(bankruptcy)	-9.23	-37.09*	31.02*		-40.44*
P(Late Payments)	-2.74	-0.16	-2.80	-3.05	
P(bankruptcy)*I_{95}	19.51	56.27*	-23.04*		61.52*
P(Late Payments)*I_{95}	12.90*	2.03*	13.68*	15.04*	
Constant	13.20*	13.98*	13.31*	13.17*	14.12*
Education loan coefficients					
Loan amount	1.58e-5*	1.59e-5*	1.54e-5*	1.48e-5*	1.37e-5*
P(bankruptcy)	-6.67	-11.76	-6.70		-0.86
P(Late Payments)	2.11	3.39	2.10	1.13	
P(bankruptcy)*I_{95}	-15.20	17.33	-9.99		20.56
P(Late Payments)*I_{95}	8.03*	1.27	8.15	5.80*	
Constant	17.19*	17.19*	17.23*	17.05*	17.20*

*Coefficients with p-values<0.1.

Table 13. Probit Selection Model Results for Base Model

1st mortgage rate				
	Coefficient	Corrected and Robust SE	t-statistic	p-value
1995 dummy	0.034	0.028	1.200	0.23
1992 dummy	-0.019	0.029	-0.640	0.52
1989 dummy	-0.005	0.032	-0.170	0.86
1983 dummy	-0.182	0.030	-5.990	0.00
Age	0.110	0.005	22.440	0.00
Age^2	-0.001	5.09E-05	-26.940	0.00
Education	0.015	0.004	4.080	0.00
Ln(income)	0.025	0.003	7.430	0.00
Married	0.409	0.023	17.610	0.00
Number of kids	0.135	0.009	14.780	0.00
Net Worth	-3.57E-08	1.59E-08	-2.240	0.03
Assets	2.95E-08	1.52E-08	1.950	0.05
No Checking Account	-0.225	0.041	-5.510	0.00
Black	-0.243	0.037	-6.630	0.00
P(Uncond. Bankruptcy)	-73.362	2.409	-30.450	0.00
$P(\text{Uncond. Bankruptcy})^2$	74.044	2.456	30.150	0.00
Borrowing is good	0.041	0.024	1.700	0.09
Borrowing is okay	0.025	0.024	1.040	0.30
Borrowing is ok for a vacation	0.042	0.028	1.510	0.13
…a cut in income	-0.124	0.019	-6.380	0.00
…fur and jewelry	0.094	0.039	2.430	0.02
…a car loan	0.277	0.028	10.080	0.00
…an education loan	-1.30E-04	0.028	0.000	1.00
Constant	-2.586	0.136	-19.050	0.00
ρ	0.127	0.031		0.00
2nd mortgage rate				
1995 dummy	-0.072	0.058	-1.250	0.21
1992 dummy	0.066	0.059	1.130	0.26
1989 dummy	0.094	0.062	1.530	0.13
1983 dummy	0.118	0.063	1.870	0.06
Age	0.053	0.014	3.750	0.00
Age^2	-5.57E-04	1.52E-04	-3.670	0.00
Education	-0.004	0.008	-0.440	0.66
Ln(income)	-0.006	0.006	-0.890	0.37
Married	0.113	0.053	2.140	0.03
Number of kids	0.032	0.017	1.940	0.05
Net Worth	-6.90E-08	2.70E-08	-2.560	0.01
Assets	6.51E-08	2.63E-08	2.480	0.01
No Checking Account	-0.034	0.115	-0.290	0.77
Black	0.064	0.088	0.730	0.47
P(Bankruptcy)	18.630	11.941	1.560	0.12
$P(\text{Bankruptcy})^2$	-777.638	645.476	-1.200	0.23
Borrowing is good	-0.030	0.049	-0.620	0.54
Borrowing is okay	0.069	0.048	1.440	0.15
Borrowing is ok for a vacation	0.088	0.054	1.620	0.11
…a cut in income	0.022	0.038	0.570	0.57
…fur and jewelry	0.056	0.071	0.790	0.43
…a car loan	0.119	0.062	1.920	0.06
…an education loan	0.054	0.060	0.890	0.37
Constant	-2.777	0.365	-7.610	0.00
ρ	-0.550	0.137		0.002

Automobile loan rate				
	Coefficient	Corrected and Robust SE	t-statistic	p-value
1995 dummy	-0.014	0.026	-0.550	0.58
1992 dummy	-0.038	0.028	-1.380	0.17
1989 dummy	0.080	0.028	2.890	0.00
1983 dummy	-0.012	0.028	-0.450	0.66
Age	0.050	0.004	11.120	0.00
Age^2	-6.65E-04	4.81E-05	-13.830	0.00
Education	-0.030	0.004	-8.240	0.00
Ln(income)	0.002	0.003	0.720	0.47
Married	0.415	0.022	18.550	0.00
Number of kids	0.027	0.008	3.480	0.00
Net Worth	-7.17E-08	1.51E-08	-4.740	0.00
Assets	5.17E-08	1.08E-08	4.770	0.00
No Checking Account	-0.599	0.038	-15.780	0.00
Black	0.088	0.033	2.660	0.01
P(Uncond. Bankruptcy)	57.121	5.110	11.180	0.00
P(Uncond. Bankruptcy)^2	-1504.797	202.210	-7.440	0.00
Borrowing is good	0.143	0.022	6.480	0.00
Borrowing is okay	0.062	0.023	2.740	0.01
Borrowing is ok for a vacation	0.020	0.025	0.780	0.44
…a cut in income	-0.099	0.018	-5.460	0.00
…fur and jewelry	0.049	0.035	1.410	0.16
…a car loan	0.796	0.034	23.660	0.00
…an education loan	-0.076	0.028	-2.730	0.01
Constant	-2.067	0.122	-16.990	0.00
ρ	-0.120	0.040		0.003
General consumer loan rate				
1995 dummy	0.164	0.039	4.240	0.00
1992 dummy	0.250	0.039	6.380	0.00
1989 dummy	0.414	0.039	10.550	0.00
1983 dummy	0.829	0.037	22.670	0.00
Age	0.012	0.005	2.440	0.02
Age^2	-2.09E-04	4.90E-05	-4.270	0.00
Education	-0.021	0.004	-4.730	0.00
Ln(income)	-0.003	0.003	-1.020	0.31
Married	0.128	0.027	4.760	0.00
Number of kids	0.053	0.010	5.290	0.00
Net Worth	-1.41E-08	2.71E-09	-5.220	0.00
Assets	1.40E-08	2.24E-09	6.220	0.00
No Checking Account	-0.196	0.039	-5.080	0.00
Black	0.223	0.037	6.100	0.00
P(Cond. Bankruptcy)	25.899	4.013	6.450	0.00
P(Cond. Bankruptcy)^2	-185.865	119.447	-1.560	0.12
Borrowing is good	0.130	0.029	4.530	0.00
Borrowing is okay	0.076	0.030	2.560	0.01
Borrowing is ok for a vacation	0.157	0.030	5.170	0.00
…a cut in income	0.041	0.023	1.830	0.07
…fur and jewelry	-0.010	0.043	-0.220	0.83
…a car loan	0.141	0.033	4.220	0.00
…an education loan	-0.015	0.033	-0.460	0.65
Constant	-1.766	0.144	-12.280	0.00
ρ	-0.561	0.063		0.000

Credit card loan rate				
	Coefficient	Corrected and Robust SE	t-statistic	p-value
1995 dummy	0.009	0.033	0.260	0.79
1983 dummy	0.079	0.038	2.080	0.04
Age	0.041	0.007	6.020	0.00
Age^2	-5.13E-04	6.57E-05	-7.820	0.00
Education	-0.068	0.006	-10.660	0.00
Ln(income)	-0.030	0.005	-6.710	0.00
Married	0.016	0.035	0.450	0.65
Number of kids	0.085	0.014	5.850	0.00
Net Worth	-7.76E-08	2.99E-08	-2.590	0.01
Assets	5.76E-08	2.91E-08	1.980	0.05
No Checking Account	-0.024	0.087	-0.280	0.78
Black	0.685	0.067	10.210	0.00
P(Uncond. Bankruptcy)	130.589	10.959	11.920	0.00
$P(\text{Uncond. Bankruptcy})^2$	-3314.063	550.115	-6.020	0.00
Borrowing is good	0.237	0.038	6.230	0.00
Borrowing is okay	0.129	0.036	3.560	0.00
Borrowing is ok for a vacation	0.264	0.041	6.430	0.00
…a cut in income	0.062	0.029	2.120	0.03
…fur and jewelry	0.117	0.058	2.010	0.04
…a car loan	0.353	0.044	8.030	0.00
…an education loan	-0.070	0.043	-1.620	0.11
Constant	-0.297	0.212	-1.400	0.16
ρ	0.104	0.093		0.267
Education loan rate				
1995 dummy	0.022	0.043	0.510	0.61
1992 dummy	-0.085	0.045	-1.900	0.06
Age	-0.024	0.008	-2.940	0.00
Age^2	3.16E-05	8.95E-05	0.350	0.72
Education	0.146	0.011	12.790	0.00
Ln(income)	-0.031	0.005	-6.840	0.00
Married	0.205	0.044	4.670	0.00
Number of kids	0.029	0.016	1.790	0.07
Net Worth	7.56E-08	9.81E-08	0.770	0.44
Assets	-8.24E-08	9.59E-08	-0.860	0.39
No Checking Account	-0.279	0.084	-3.330	0.00
Black	0.198	0.066	3.020	0.00
P(Uncond. Bankruptcy)	62.237	7.745	8.040	0.00
$P(\text{Uncond. Bankruptcy})^2$	-1119.720	270.259	-4.140	0.00
Borrowing is good	-0.077	0.047	-1.650	0.10
Borrowing is okay	-0.043	0.045	-0.940	0.35
Borrowing is ok for a vacation	0.122	0.051	2.390	0.02
…a cut in income	0.079	0.037	2.110	0.04
…fur and jewelry	0.079	0.067	1.180	0.24
…a car loan	0.064	0.056	1.150	0.25
…an education loan	0.519	0.075	6.950	0.00
Constant	-3.255	0.253	-12.840	0.00
ρ	-0.036	0.070		0.607

Table 14. Premium Spreads Using Model of Interest Rate Determination

	A	*l*	*o*	*f*	*T*	*Premium Spread*
1st Mortgage Rate*	$86,000	.7	7.0%	1000	30 years	0.33
2nd Mortgage Rate	25,000	.4	8.7	350	10	0.67
Auto Loan Rate	12,000	.4	7.7	240	5	0.66
General Consumer Loan Rate	1,550	.05	10.3	105	1	1.14
Credit Card Loan Rate	2,000	.05	14.2	105	1	1.16
Education Loan Rate	7,700	.2	8.3	140	10	0.89

* For tractability, default risk is only assessed through twenty years. The impact on the risk premium is minimal.

Table 15. Premium Spreads using Alternative Parameter Values

	A	*l*	*o*	*f*	*T*	*Premium Spread*
1st Mortgage Rate	$86,000	.4	7.0%	1000	30 years	0.66
1st Mortgage Rate	$86,000	.4	7.0%	1500	30 years	0.66
2nd Mortgage Rate	25,000	0	8.7	350	10	1.11
2nd Mortgage Rate	25,000	0	8.7	500	10	1.12
Auto Loan Rate	12,000	0	7.7	240	5	1.11
Auto Loan Rate	12,000	0	7.7	300	5	1.11
General Consumer Loan Rate	1,550	.2	10.3	105	1	0.95
General Consumer Loan Rate	1,550	.2	10.3	50	1	0.92
Credit Card Loan Rate	2,000	0	14.2	105	1	1.22
Credit Card Loan Rate	2,000	0	14.2	140	1	1.24
Education Loan Rate	7,700	.4	8.3	140	10	0.66
Education Loan Rate	7,700	.4	8.3	50	10	0.65

Figure 1. Predicted Interest Rates plotted against Conditional Bankruptcy Risk

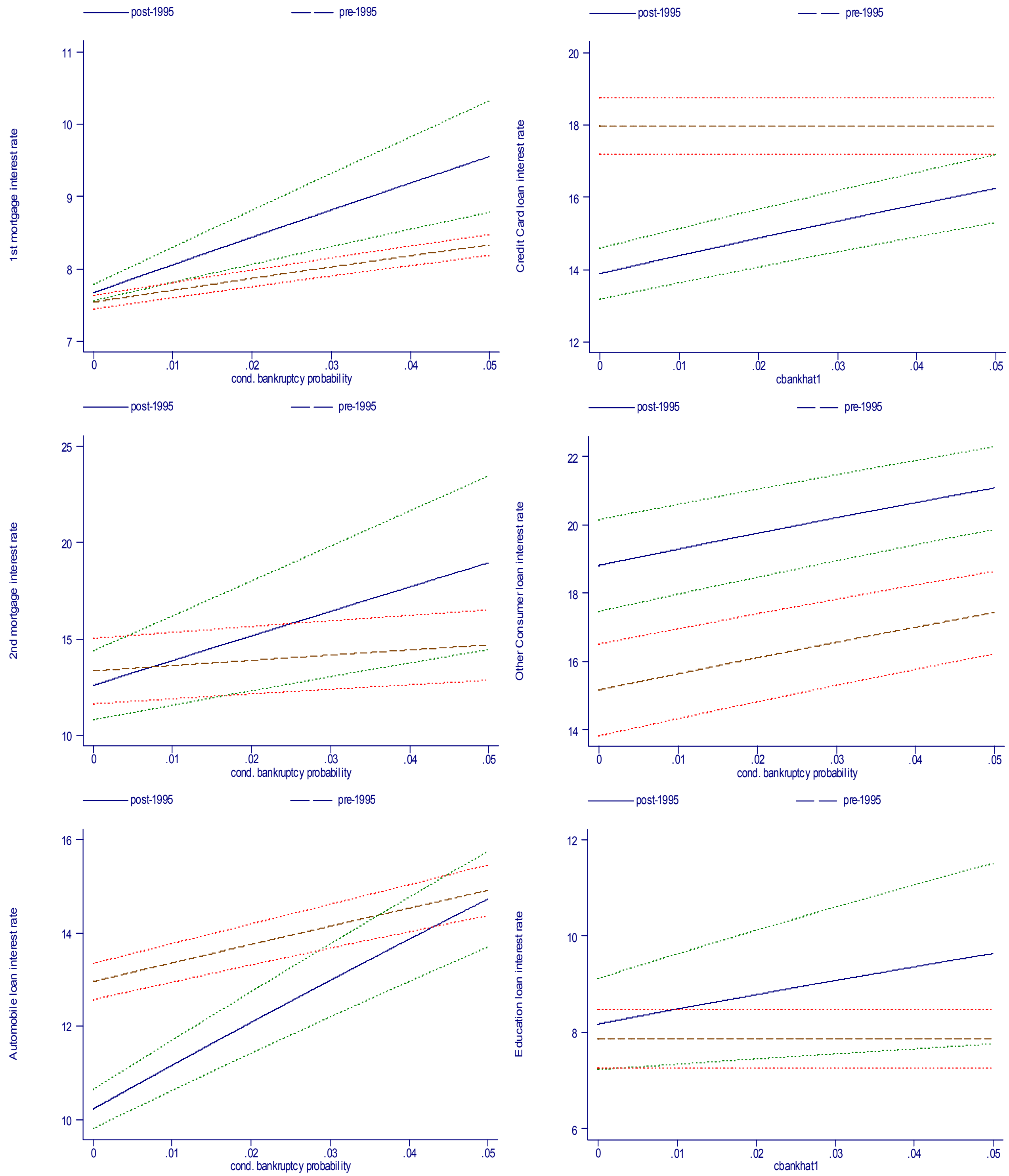
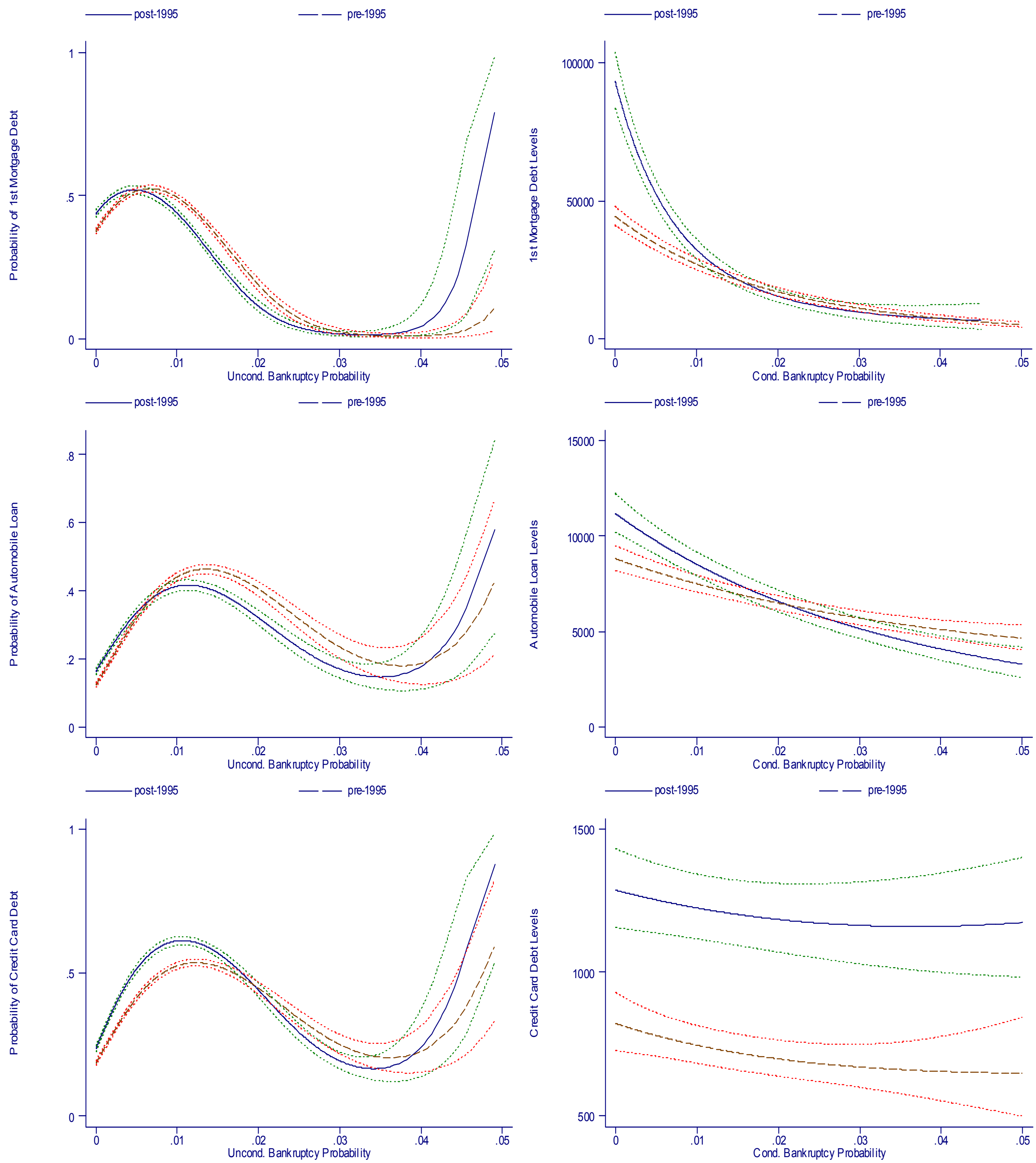
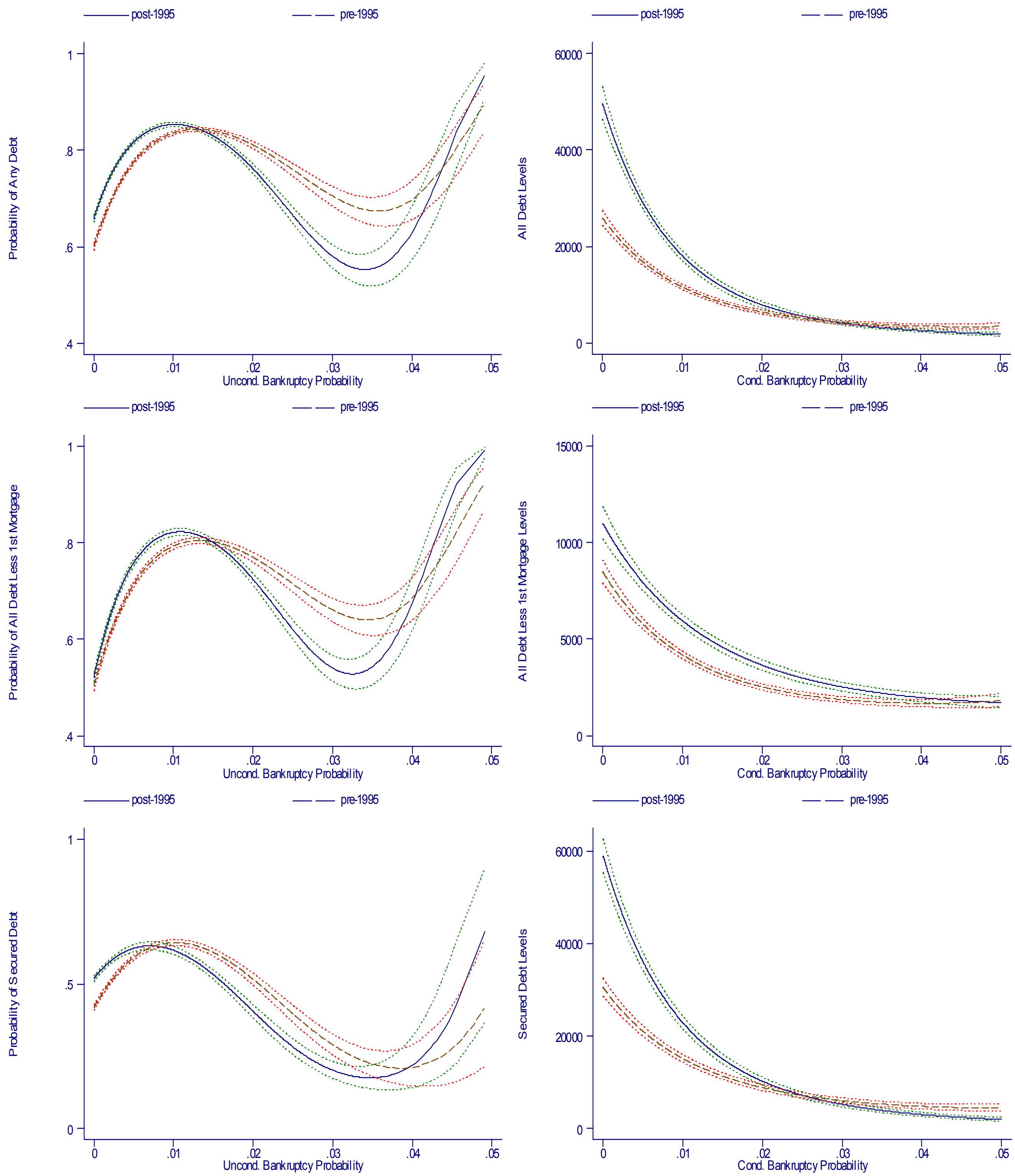


Figure 2. Predicted Probabilities of Holding Debt and Debt Levels plotted against Bankruptcy Risk





post-1995
pre-1995
Probability of Any Debt
Uncond. Bankruptcy Probability
All Debt Levels
Cond. Bankruptcy Probability
Probability of All Debt Less 1st Mortgage
All Debt Less 1st Mortgage Levels
Probability of Secured Debt
Secured Debt Levels

Figure 3. Estimated Effects of Risk-Based Pricing

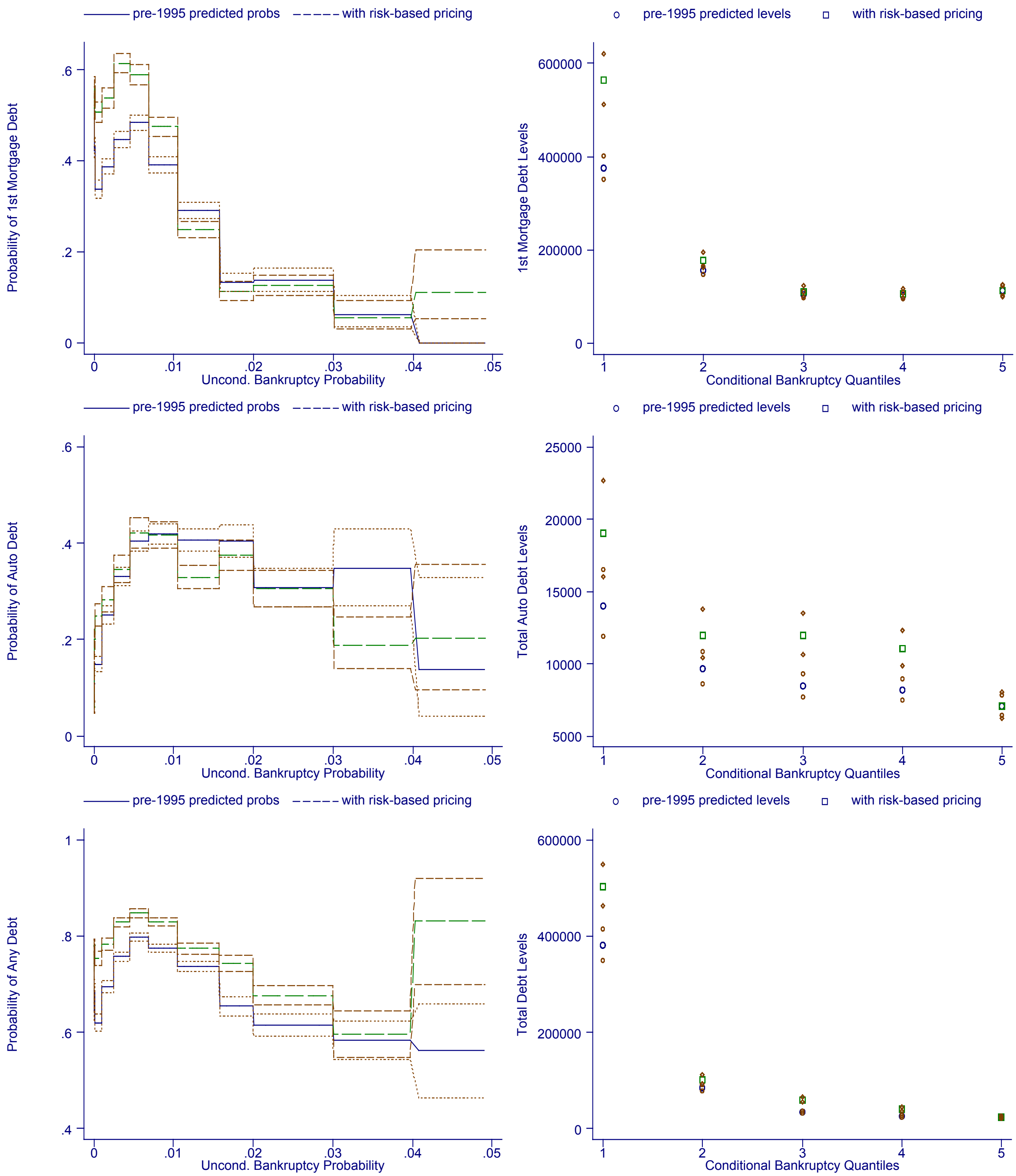


Figure 4. Interest Rate Predicted in Theoretical Model