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Competition Between Banks and Finance Companies: A Cross Section Study of Personal Loan Debtors

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COMPETITION BETWEEN BANKS AND FINANCE COMPANIES: A CROSS SECTION STUDY OF PERSONAL LOAN DEBTORS

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I. INTRODUCTION

Consumer activism in recent years has resulted in numerous laws and regulations designed to protect the consumer in the marketplace. For example in the consumer credit field, truth-in-lending was legislated, wage garnishment was restricted, holders' liability on credit cards was limited, disclosure of credit reports was required, and so on. Nevertheless, it still remains that competition is an important means of assuring the best possible terms to credit users.

Because banks and finance companies are the largest suppliers of consumer credit, it follows that the degree of competition between the two will have an important influence on the competitiveness of consumer credit markets in general. Therefore, this paper examines the question of whether competition between banks and finance companies for consumer credit customers is limited by market segmentation on the basis of customer risk.[1] This study of market risk segmentation will have important implications for the merger analysis conducted by the Federal Reserve Board which has responsibility for evaluating the competitive effects of mergers between bank holding companies and finance companies.

II. MARKET RISK SEGMENTATION

Consumer credit researchers have generally believed that the market for consumer credit is substantially segmented on the basis of risk ([5], pp.128-129; [22], pp.29-31). That is, banks supposedly serve low risk borrowers while finance companies cover the high-risk borrowers. This market risk segmentation is thought to be caused by regulatory constraints and the historical practices of the two industries ([5], pp.128135; [8], pp.1444-1445). Regulatory limits have been placed on interest rates, loan size, and entry. As for industry practices, banks historically have served business and commerce while emphasizing stability and soundness. Finance companies have evolved with the express purpose of serving the credit needs of low and middle-income individuals.

In this study survey data on the socio-economic and life cycle characteristics of credit users are used to examine the hypothesis that the two institutions segment the market by serving different risk classes of borrowers. The data are from a 1970 national survey of consumers that was sponsored by the Federal Reserve Board to measure the effectiveness of Truth-in-Lending.[2] Computerized random sampling techniques were used

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* *Economist, Board of Governors of the Federal Reserve System. The views of this paper do not necessarily reflect the views of the Board or its staff. I acknowledge the helpful comments on an earlier draft from Robert Eisenbeis, Gerald Hanweck, Robert Johnson, Richard Peterson, Stephen Rhoades, and James Smith. I thank Ronald McWilliams, Marcia Morrell, and especially Nancy Pittman for manipulating the computer.

[1] The risk segmentation hypothesis is typically stated in terms of borrower characteristics with the implication that the riskiness of the loan package-that is, the borrower characteristics and loan terms--reflects the riskiness of the borrower. It is possible that the two institutions serve different risk classes of customers but alter the loan terms so that the loan packages have comparable risk. However, there is no empirical support for this possibility ([2], pp. 151-152).

[2] For a description of the 1970 sample and questionnaire, see Shay and Schober ([24], pp. 55-82). (Note that Appendix Table 9 of [24] is the 1970 questionnaire; it is incorrectly labeled the 1969 questionnaire.) In the survey, if an individual had more than one personal loan, he was questioned about the largest one. Although the number of individuals with loans at both institutions is not known, it is thought to be a small proportion of the entire sample.

to select sample households. The sample drawn for the 1970 survey was reasonably representative of the United States ([24], pp.59-60).

Statistical techniques are used to compare the characteristics of those survey respondents whose largest outstanding personal loan was held by a bank to those whose largest outstanding personal loan was held by a finance company. The characteristics investigated--age, home ownership, credit-card ownership, number of dependents, marital status, education, race, income and sex--have frequently been included in credit-evaluation models to discriminate between credit-worthy and risky borrowers. Of course, if risk segmentation occurs, one would expect the risk-related characteristics of finance company borrowers to differ generally from those of bank borrowers.

At this point, two key assumptions of the study must be noted.[3] Since the basic issue is whether there is substantial overlap of risk and since risk cannot be directly measured, it is postulated that varables like age, income, and education accurately mirror risk. And not only is it assumed that the selected borrower characteristics and risk are closely correlated, but also it is supposed that the relationship between risk and those characteristics is the same for patrons of the two institutions.

The first assumption of a close tie between observed attributes and risk may be violated if, for example, those borrower factors do not correctly portray "character," presumably an important determinant of credit worthiness which may be a complex function of past experiences, customer familiarity, personal impressions, and other relationships with the customer. In such a case, the model is misspecified and a finding, say, of substantial overlap between classes of customers would be undermined.

The second assumption of a symmetric relationship between risk and the two kinds of borrowers would not hold if consumers, using past experience or conversations with friends, self-select themselves on the basis of past payment experience, indebtedness, expected income, and so forth, and apply at the institution judged most likely to accept them. In this situation, high income, let us say, could be a favorable factor for banks but an unfavorable one for finance companies because only high-income borrowers with poor payment histories and heavy indebtedness seek out finance companies.

The above reservations evidently will temper the empirical findings. Nonetheless, because the risk-related attributes used in this study have been used in numerous credit scoring models, it is felt that they may be useful in evaluating the relative riskiness of different credit users. Given the assumption that data on borrower age, sex, race, marital status, income, dependents, home ownership, and credit card ownership are sufficient to determine whether finance companies and banks service distinctly different markets based on customer risk, it follows that analysis of these data obtained from survey respondents would indicate whether finance company and bank borrowers fall into two distinct risk classes.

This approach to the question of risk segmentation (and thereby inter-industry competition) has several advantages over earlier research that used state data and focused upon cross elasticities with respect to the loans of the two industries.[4] First, by employing information on individual borrowers, one avoids using data aggregated at the state level. Statewide aggregate data may gloss over details of inter-industry competition. Second, by looking at the overlap in borrower characteristics, one implicitly allows for price and non-price forms of competition or segmentation. For instance, such data can show whether market segmentation exists in spite of the fact that lenders could conceivably make loans at different terms to borrowers of different risk.

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[3] I thank William Dunkelberg of the Credit Research Center for emphasizing these reservations.

[4] Earlier research by Eisenbeis and Murphy [7] also used survey data on individual borrowers to examine the risk segmentation hypothesis. See Boczar [2] for a survey of earlier research on cross elasticities.

Finally, the study focuses upon the risk segmentation hypothesis in a multivariate context. With this approach, even though complex and interrelated demand and supply forces are at work, it is not necessary to attempt the difficult job of separating demand and supply forces. That task is required if one wanted to estimate cross elasticities in getting at the question of inter-industry competition.

III. SURVEY DATA ON BORROWER CHARACTERISTICS

Survey data on personal loan[5] customers at banks and finance companies are used for testing purposes. By considering only personal loan borrowers, one avoids the complications of a joint product where credit is closely tied to the purchase of a consumer good. When consumer credit is closely tied to consumer purchase, as with credit from retailers, it is most difficult to separate the attractive features of the purchase from the characteristics of the associated credit. Moreover, if banks and consumer finance companies compete, it is most likely to be in the personal loan area since these types of loans represent 80 to 85 percent of the loan receivables of consumer finance companies [3],[4].[6]

It should be noted that borrowers with initial personal loans of $25,000 or more are excluded from the sample since such loans are probably business or investment loans, not consumer loans. Since finance companies usually do not make single payment personal loans, these loans are also excluded.

Data from the 1970 survey show whether the debtor is a homeowner, a credit card holder, as well as age, number in household, marital status, education, race, income, and sex. These data, most of which are customarily employed in credit scoring models [1], [21], [23], [25], are used to associate risk-related borrower characteristics with the clientele of the two institutions.

Specifically, homeownership is a measure of consumer wealth and perhaps consumer stability, with homeowners considered a less risky group than renters. Possession of credit cards from gasoline companies or retail stores suggests that the individual has used credit properly in the past and has a good credit report. Age and marital status are thought of as measures of income stability with the young and the single considered to have less stable income flows. Education is correlated with human wealth and expected income flows of the prospective debtor. Current income is a rough measure of the borrower's ability to repay a loan. Other things equal, the more household members, the less able is the potential borrower to repay a specified loan. Finally the data on race and sex conceivably could measure systematic risk or market-segmentation criteria not accounted for by the other variables.[7] (See Table I for a definition of variables and their mean values.)

Note that those borrower characteristics appear to be "objectively" determinable and easily remembered by the interviewee. Because nonreporting for these data fields in the survey was always below three percent, one need not worry about significant nonsampling errors associated with high frequencies of nonreporting in many consumer surveys [10], [11].

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[5] Personal loans are defined as direct cash loans made on an installment basis to individuals and families.

[6] Throughout the paper, the term "finance company" is used as a synonym for consumer finance company; that is a company that is heavily engaged in personal cash lending. The risk segmentation hypothesis has traditionally been applied to consumer finance companies. It has usually not been alleged that banks and sales finance companies, particularly the captive companies, engage in risk segmentation.

[7] 1n an early study, Durand [6] found that women were a better credit risk, but this finding may result from the fact that he was dealing only with accepted credit applicants.

IV. STATISTICAL METHODS

The dependent variable in the study is dichotomous: the borrower obtained a personal loan from a bank or a finance company. Regression analysis with a dichotomous dependent variable will result in heteroskedastic error terms. Therefore, ordinary least squares estimators, although unbiased, are not efficient. Second, because the disturbance terms is not normally distributed, the OLS estimators are not normally distributed, and thus the classical tests of significance do not apply ([19], pp. 425-427).[8]

There are several techniques available to handle dichotomous dependent variables. The method used in this study is multivariate probit analysis ([12], p. 28).[9] The probit model is used to estimate the probability (P) that a borrower obtained a loan from a bank, based on various characteristics of the borrower. Details of probit analysis are set forth in the appendix.

Table 1. - Variables and Their Mean Values

	Variable	Mean Value All Debtors	Mean Value Bank Debtors	Mean Value Finance Debtors
	Borrower Characteristics			
HO.	Homeownership (1 = owns home; 0 otherwise)	0.65	0.73	0.47
CC.	Credit Card (1 = has credit card of gasoline company or retail store; 0 otherwise)	0.75	0.81	0.61
$A_{}$	Age 18 to 24 (Excluded Category)[a]	0.09	0.07	0.11
A_y	Age 25 to 34 (1 = in age group; 0 otherwise)	0.30	0.26	0.38
A_m	Age 35 to 49 (1 = in age group; 0 otherwise)	0.38	0.38	0.39
A_o	Age 50 and over (1 = in age group; 0 otherwise)	0.23	0.29	0.12
NH.	Number in Household	3.93	3.94	3.90
M.	Marital Status (1 = married; 0 otherwise)	0.84	0.88	0.76
$E_{}$	Grade School or Less Education (Excluded Category)	0.10	0.10	0.10
$E_{hs.}$	Some or Graduated High School (1 = in group; 0 otherwise)	0.53	0.47	0.67
$E_{c.}$	Some or graduated College (1 = in group; 0 otherwise)	0.37	0.43	0.23
R.	Race (1 = white; 0 therwise)	0.85	0.92	0.71
$Y_{}$	Income under $5,000 (Excluded category)	0.11	0.10	0.14
$Y_{m.}$	Income $5,000 or $10,000 (1 = in group; 0 otherwise)	0.42	0.37	0.53
$Y_{u.}$	Income $10,000 and over (1 = in group; 0 otherwise)	0.47	0.53	0.33
S.	Sex (1 = male; 0 = female)	0.88	0.92	0.81
	Dependent Variable			
Y.	Source of Personal Loan (1 = bank; 0 = finance company)	0.69	1.0	0.0

[a]Given a separate intercept term, it is necessary to exclude one category when using dummy variables to measure the effects of three or more levels of a factor (such as education) in order to avoid a linear dependence in the data matrix [27].

V. EMPIRICAL FINDINGS

Using probit analysis, the following relation was estimated:

$$P = F\,[HO,CC,A,NH,M,E,R,Y,S,U] \qquad (1)$$

[8] 0ne would like a measure of borrower indebtedness, but useable information was not collected.

[9] An attempt was also made to estimate the relationship using a generalized least squares procedure suggested by Goldberger ([161, p. 250). However, the estimates were very sensitive to the boundary values assigned to the predicted Y's that fell outside the 0-1 interval.

Where:

P = Probability the borrower obtained credit from a bank,[10]
U = Random differences with a normal distribution.
Explanatory variables are defined in Table 1.

Estimates for Lender-Borrower Relation

The probit estimates are reported in Table 2. The likelihood ratio is highly significant, thereby implying that the profile of bank debtors is different from that of finance company debtors. Such differences could result from differential credit rationing by different classes of lenders and from the fact that certain classes of potential borrowers preferentially applied for credit from a particular type of lender.

The empirical findings showed homeowners (HO) and holders of nonblank credit cards (CC)[11] to be more likely to obtain credit from banks than finance companies. The age variables were significant as a class, with banks lending to older borrowers (A_0) and finance companies lending to younger borrowers (A_y). Number in household (NH) and marital status (M) were not significantly different from zero, but borrowers from larger households and riskier marital status groups were more likely to be finance company borrowers. Education of the debtor possessed a highly significant likelihood ratio, with college-educated individuals (E_c) being served by banks and high school-educated persons (E_{hs}) being served by finance companies. The high significance of race (R) suggests that nonwhites were less likely to obtain credit from banks than finance companies after control ling for other characteristics.

Table 2
Probit Estimates for Lender-Debtor Relation

P=	-0.864	+	0. 525HO	+	0. 391 CC	-	0. 235A_y
	(1.80)[b]		(2.86)[a]		(2.14) [b]		(0.78)
	-0.031A_m	+	0.590A 0	-	0.023NH	+	0.325M
	(0.10)		(1.68) b		(0.48)		(1.10)
	-0.485E_{hs}	+	0.183E C	+	0.755R	-	0.082Y_m
	(1.40)		(0.49)		(3.16)[a]		(0.28)
	+0.047Y_u	+	0.179S		Likelihood Ratio		
	(0.14)		(0.54)		(df =13) :74.85		

Note: Values in parentheses are t-values (one-tailed test). The t-values for the dummy variables representing levels of a factor (age, education, and income) test for significant differences in effect, compared with the excluded level. The likelihood ratios below test the joint hypothesis that all dummy variables representing a particular factor possess coefficients not significantly different from zero. The likelihood ratios are: Age (df=3) = 10.60[b] ; Education (df=2) = 14.21[a] ; Income (df=2) = 0.50. Since only data on borrowers are used, it is not necessary to weight data for the fact that non-borrowers were not fully sampled ([24], p. 62).

[a]Significant at the 0.01 level.
[b]Significant at the 0.05 level.

[10] Of course, 1-P equals the probability that a borrower obtained credit from a finance company. Note also that the observed outcome (Y=l or 0) is used to estimate P, the probability of the outcome, which is unobservable.
[11] The discussion is couched in terms of lending institutions. Of course, the estimated relationship reflects the interaction of lenders and borrowers.

No evidence was found to support the hypothesis that banks typically supply credit to high-income persons and finance companies usually supply funds to lower-income persons. However, long-run permanent income, rather than current reported income, may be a better measure of ability to repay [14]. Unfortunately, convincing estimates of permanent income were not obtainable from the survey data.[12] Finally, no evidence was uncovered linking credit source to borrowers' sex (S).

Predictive Accuracy of Estimated Relation

The empirical results clearly show that the borrower profiles differ between the two industries. The results thus are consistent with the risk segmentation hypothesis in the sense that finance company borrowers more frequently exhibit traditional risky characteristics than bank borrowers. The task now is to investigate the extent of overlap, if any, between the two profiles.

As a first step in this investigation, the relative frequency distribution of estimated probabilities for each institution's customers is displayed in Figure 1. The probit probabilities (P) shown on the horizontal axis were estimated for each borrower from the relationship shown in Table 2. These probabilities are calculated from the various indices of risk (borrower characteristics) and show the probability that a customer will be from a bank, rather than from a finance company. The frequency with which bank borrowers and finance company borrowers achieved these indices is shown on the vertical axis. Thus about 20 percent of bank borrowers had "scores" or P-values in the range of .90 to .95, whereas only five percent of borrowers from finance companies had P-values in this range. If all borrowers having an estimated probability (P) greater than 0.5 are classified as bank borrowers, and all with a probability less than 0.5 as finance company borrowers, nearly 25 percent of the original sample of 325 is misclassified. Moreover, finance company borrowers are about nine times more likely to be misclassified than bank borrowers. (See top half of Table 3.)

Of course, it is necessary to use new data to get at the predictive accuracy of the model. If the same data set is used to estimate parameters and to test for predictive accuracy, the resulting predictions will be biased. This bias results from the fact than any one sample may not be entirely representative of the population combined with the fact that the estimates best fit the sample under study. Thus, predictions based on the original sample may overstate the "true" accuracy of the estimated model [13].[13]

Unfortunately, while use of a holdout sample removes the above bias, it also reduces the size of the sample employed to estimate parameters. In this case, the sample size (n=325) is not overly large and in view of the qualitative character of the data matrix, it is desirable to use the largest sample possible to estimate parameters ([4], pp. 546-547). Accordingly all observations were used to estimate the lender-borrower equation displayed in Table 2.

To judge predictive accuracy (and thereby, the extent of overlap in borrower characteristics) equation (1) was re-estimated after randomly selecting a holdout sample of 75 observations from among the original sample of 325 observations. Then the estimated model was applied to the holdout sample and the proportion of correct classifications of outcomes using a 0.5 rule was calculated. This procedure was replicated 25 times and the results summed to give an aggregate "holdout" sample of 1,875.[14]

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[12] See Stafford and Dunkelberg [26] for an attempt to obtain a measure of permanent income from survey data.

[13] The bias may be substantial. Eisenbeis and Murphy [7] used multivariate discriminate analysis to evaluate a survey of consumer credit customers from the state of Maine. Reclassifying the original sample resulted in 26.3 percent of the observations being misclassified. Use of an almost unbiased holdout sample increased the proportion of misclassifications by almost 15 percentage points.

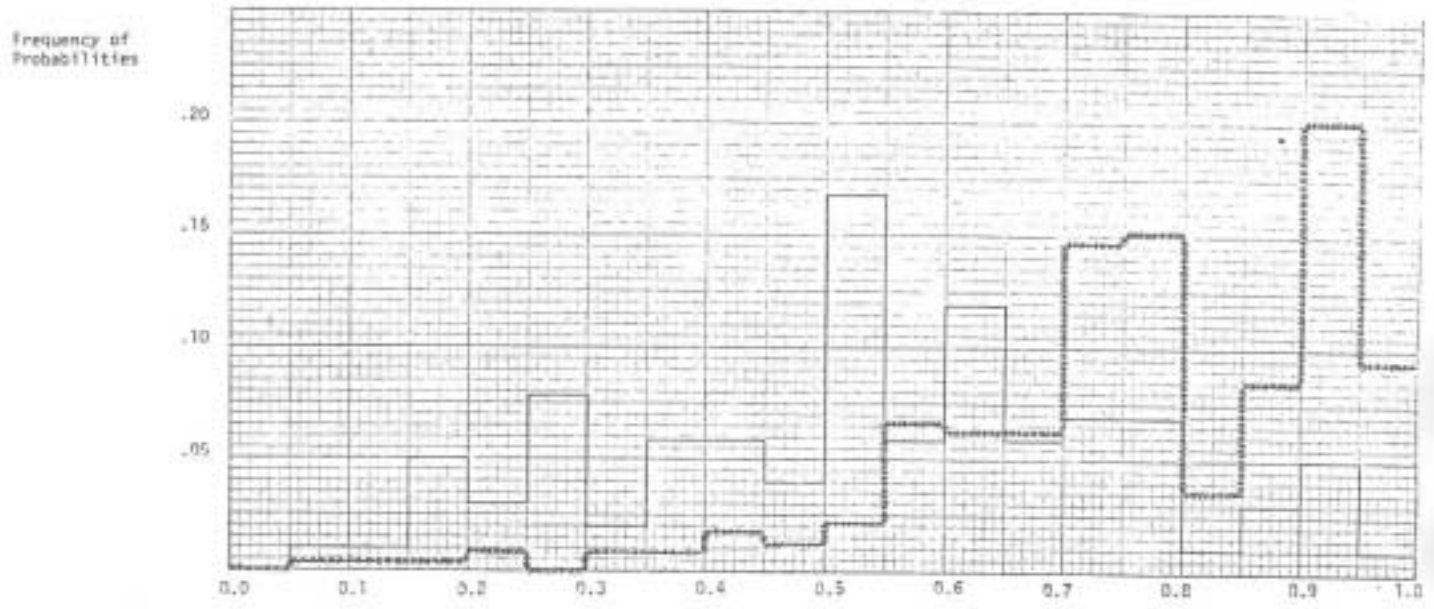
[14] Two things are attempted with this procedure: (I)to obtain an unbiased measure of the predictive accuracy of the model; and (2) to exhaust the information content of the sample. The properties of this method are not well known but it seems a reasonable one. For an

Table 3. - Prediction Results

Original Sample		Predicted Group Membership	
Actual Group	**Total**	**Bank Borrower**	**Finance Company**
Bank	224	208	16
Borrower	(100.00%)	(92.865)	(7.14%)
Finance Company	101	65	36
Borrower	(100.00%)	(64.36%)	(35.64%)
Observations Misclassified:	81 (24.92%)		

Holdout Sample		Predicted Group Membership	
Actual Group	**Total**	**Bank Borrower**	**Finance Company**
Bank	1,299	1,182	117
Borrower	(100.00%)	(90.99%)	(9.01%)
Finance Company	576	392	184
Borrower	(100.00%)	(68.06%)	(31.94%)
Observations Misclassified:	509 (27.15%)		

Figure 1. Distribution of Estimated Probabilities (P) for Borrowers from Banks and Finance Companies - Original Sample



*A probability is determined by first substituting a borrower's characteristics into the estimated equation of Table 2 to obtain a value for I. The area under a unit normal curve at the I-value, which area is found in a cumulative normal distribution table, equals the probability, P.

earlier application of this procedure, see [13]. For a similar procedure in discriminate analysis where the holdout sample is a single observation, see Lachenbruch [18].

This replicated holdout sample method misclassified 27.15 percent of the observations, compared to 24.92 percent with the original sample. Again, finance company borrowers were much more likely to be misclassified. (See bottom half of Table 3.) Figure 2 reflects the relative frequency of the 1,875 estimated probabilities. The two distributions--one for bank borrowers and one for finance company borrowers--are similar to the two distributions based on the original sample, except that some of the sharp peaks of the original sample distributions have been smoothed.

Now we need a confidence interval for the proportion of correct classifications. Let P(C) represent the proportion of correct classifications in one holdout sample. The mean of P(C) for the 25-holdout samples is 0.7285 and standard deviation for P(C) is 0.0102.[15] A 95 percent confidence interval for the average proportion of correct classification is then (0.7083, 0.7487). Based on this 95 percent confidence interval, we are on safe ground in concluding that the estimated relationship misclassified slightly more than one out of every four debtors in the sample. To put it another way, over one-fourth of the customers of one or the other of these two credit grantors had risk-related characteristics which we determined from the probit analysis were more closely identifiable with the market hypothesized to be served by the other lender.

However, three major qualifications would affect a conclusion that there is in truth a substantial overlap in the risk characteristics of borrowers served by the two institutions. First, the true probabilities that consumers will choose one or the other lender are not directly observable. (For instance, the true probability of a customer being a bank borrower may be 0.9, but the outcome observed is, say, one--the customer is a bank borrower.) Because the observed outcomes--zero or one--are used for estimation, the estimates are subject to error. Moreover, in a recent paper, Morrison [20] has shown that the expected value of P(C)--the proportion of correct classifications--is typically less than one. In other words, even if we know the true distribution of probabilities, we would not be able to correctly predict outcomes all of the time.[16] Thus, misclassifying one fourth of the outcomes results at least partially from the fact that the true probabilities of action are unobservable.

Second, bank borrowers appear over represented in the sample compared to the population.[17] Bank debtors comprise 69 percent of the sample while Federal Reserve data for the same time ([9], pp. A47-A48) show banks hold about 45 percent of the dollar value of personal loans outstanding at the two institutions. If for instance, the sample contained an even split of borrowers between the two institutions, the total percentages of misclassification from the holdout samples might rise. Assuming that misclassifications of individual borrowers remain the same (9.01 percent for bank borrowers and 68.06 percent for finance company borrowers), if half the borrowers were drawn from each institution and all coefficients remained the same, the aggregate misclassification percentage would rise from 27.15 percent to 38.54 percent.

Third, the market overlap that we observed is based solely on the probabilities that borrowers with certain characteristics will both apply to and borrow from a particular lender. These probabilities were obtained from our probit analysis of a limited set of borrower characteristics. If, in fact, different lenders use different characteristics in their credit evaluations, or if they weigh the characteristics which we used differently, they might be able to segregate borrowers in our overlapping groups, even though we cannot.

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15 For more detailed discussions, see Morrison [20] and Westin [29].

16 For example, given that the true distribution of probabilities is uniform, Morrison [20, 70] found the expected value of P(C) to be 0.75. Hence, the best we can do in this situation, on the average, is correctly predict three-fourths of the outcomes. Also, see Goldberger [15] for a comment on the sample value of P(C) as contrasted with its expected value.

17 Although bank borrowers seem over represented, it can be argued that the sample gives unbiased estimates of the relationship of borrower characteristics to loan source even though the sample gives biased estimates of the separate frequency distributions of the variables.

While keeping in mind these qualifications, one must be impressed with the fact that two out of every three finance company customers have "risk related" characteristics which we determined were highly similar to those of bank customers. It seems reasonable to conclude that the evidence on borrower characteristics does not support the risk segmentation hypothesis.[18] Therefore, based on our evaluation of the sample data, market risk segmentation does not appear to be an effective impediment to inter institutional competition.

VI. SUMMARY, CONCLUSIONS, AND FUTURE RESEARCH

The study was designed to examine the hypothesis that consumer credit market competition is limited because the market for consumer credit at banks and finance companies is segmented on the basis of customer risk. Data from a national survey of households were used to determine the socioeconomic and life-cycle characteristics of borrowers at the two loan sources. These characteristics were used as proxies for the riskiness of the two groups of borrowers.

Multivariate probit analysis was used to estimate the likelihood that the two institutions supplied credit to patrons with different (risk) characteristics. The empirical results showed that the borrower profiles differed between the two industries. However, further analysis of the results revealed that there was substantial overlap in borrower characteristics between the two industries, largely due to the fact that finance companies served borrowers whose risk-related characteristics, based on our analysis, were similar to the risk-related characteristics of bank borrowers. This conclusion, of course, depends on the assumption that we used appropriate risk-related characteristics in our analysis and weighed them properly.

The finding of substantial overlap in customer attributes for the sampled households implies that the market is not being segmented on the basis of risk; and therefore, that risk segmentation is not an effective barrier to inter industry competition. Absent other barriers, it follows that the market for consumer credit is likely performing well in serving consumer-borrowers. Finally, the results suggest that the Federal Reserve Board should be concerned with the possible elimination of existing competition in mergers between bank holding companies and finance companies.

In view of the reservations noted earlier, however, these empirical results must be judged tentative. Future research on market risk segmentation ideally should include survey questions to determine whether individuals consider patronizing both types of institutions and additional measures of borrower characteristics that could get at the question of borrower "character." Additionally, control variables may be needed to adjust for state and/or regional differences in regulation and the weights assigned to the risk proxies. And a measure of borrower debt outstanding is clearly called for. Researchers could also consider the use of interaction terms as well as other classification rules. Another approach in subsequent research would be to use the credit data and credit experience of the two institutions to decide if the connection between borrower attributes and risk is consistent across the two types of lenders.

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[18] This conclusion is consistent with the sharp decline in the finance industry's share of personal loans. In 1965 finance companies held 49.7 percent of personal loans outstanding in the U.S. while banks held 31.4 percent of the total. By the end of 1974, the finance industry's share had declined to 38.8 percent while the banks' share had climbed to 34.8 percent. The share held by credit unions also grew at the expense of finance companies ([9], pp. A47-A48).

The decline in the national share of finance companies is consistent with the following scenario: The implementation of truth-in-lending, a rise in consumer awareness, and the increased aggressiveness of banks has resulted in finance company customers, the majority of which are bankable according to our study, seeking and obtaining credit from lower-rate banks and credit unions. This scenario supposes a blend of supply and demand adjustments over the past ten years.

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APPENDIX

Explanation of Probit Analysis

The probit model supposes that there is an index I, which is a linear combination of various independent variables $X_1, X_2, \ldots X_m$ that determine whether the dependent variable Y has the value 0 or I for a borrower.

$$I = B_O + B_1 X_1 + \ldots\ldots + B_M X_M = X'B \qquad (1)$$

Let I_i be the actual value of the index of the i^{th} borrower,, where the values of the independent variables for the i^{th} borrower and the estimated coefficients (determined below) are used to calculate I_i. Let I_i be the critical value of the index for the i^{th} borrower. If the actual value of the index I_i equals or exceeds the critical value I_i. then Y_i will be 1; if I_i is less than I_i , then Y_i will be 0.

$$Y_i = 1 \text{ for } I_i \geq T_i \qquad (2)$$
$$Y_i = 0 \text{ for } I_i < T_i$$

Over the population of borrowers and lenders, the critical values I_i are assumed to be normally distributed with mean zero and unit variance. This distribution reflects random differences among borrowers and lenders, differences in personality and taste for example, that are not represented by any of the variables in the index. [28, 4-5].

This model implies that the probability of being a bank borrower, P(B) can be written:

$$E(Y/X) = P(B) = 1/\sqrt{2\pi} \int_{-\infty}^{X'B} \exp(-u^2/2)\, du \qquad (3)$$
$$= F(X'B) = F(I)$$

where F(.) denotes the cumulative normal distribution function. The probit coefficients are estimated with an iterative maximum likelihood technique. The estimated coefficients are used to calculate values of I (as described above) which in turn are transformed into probability estimates, P, via the cumulative normal distribution [17, 82]. [19]

[19] Another way to handle dichotomous events is to use multivariate discriminate analysis (MDA). This technique is especially appealing for this study because MDA is well suited to determine the extent of overlap in borrower profiles. Unfortunately, classical tests of hypotheses cannot be applied to MDA's findings because the assumption of a multivariate normal data matrix (borrower characteristics) is not even remotely satisfied, all but one of the borrower attributes being binary-valued.

The probabilities estimated by the probit method are nonlinear functions of X even though the probit index is linear in X. Thus, the effect of a unit change in an explanatory variable upon the probability depends on the particular value of the probit index [17, 82]. To illustrate, the changes in probabilities (P) are evaluated at selected values of the probit index (I)--that is, at selected points on the cumulative normal distribution-using the probit equation estimated in the text. The selected points displayed in Table 1 on the next page correspond to two low probabilities of the event occurring (0.10 and 0.30), two high probabilities (0.80 and 0.90), and the average probability of the event occurring in the sample (0.689).

Table 1 illustrates that in the cases where the outcome of the event seems certain (P of 0.10 or P of 0.90) the explanatory variables have a smaller impact on changing the probability than the cases where the outcome is less certain. Note, however, that some variables that have a positive (negative) impact can be significant in increasing (reducing) the probability when it is at a low (high) level.

Table 1 - Change in Probability Evaluated at[a]

Variable Name	**Probit Coeff.**	**P = 0.10 I = -1.28**	**P = 0.30 1 = -0.52**	**P = 0.689 1 = 0.49**	**P = 0.80 1 = 0.84**	**P=0.90 1=1.28**
HO	0.52	0.12	0.20	0.15	0.11	0.06
cc	0.39	0.09	0.15	0.12	0.09	0.05
A_y	-0.24	-0.04	-0.08	-0.09	-0.07	-0.05
A_m	-0-03	-0.01	-0.01	-0.01	-0.01	-0.01
A_0	0.59	0.15	0.23	0.17	0.12	0.07
NH	-0.02	-0.00	-0.01	0.01	-0.01	-0.00
M	0.33	0.07	0.12	0.10	0.08	0.05
E_{hs}	-0.49	-0.06	-0.14	-0.19	-0.16	-0.11
E_c	0.18	0.02	0.07	0.06	0.05	0.03
R	0.75	0.20	0.29	0.20	0.14	0.08
Y_m	-0.08	-0.01	-0.03	-0.03	-0.02	-0.02
Y_u	0.05	0.01	0.02	0.02	0.01	0.01
S	0.18	0.02	0.07	0.06	0.05	0.03

[a] Changes in probabilities ' were obtained from the cumulative normal distribution table. P is the probability estimate associated with each probit index I. P = 0.689 represents the average probability of being a bank debtor in the sample.