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Bank Loan Rate Clustering: Theory and Evidence*

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ABSTRACT

In this paper, we provide a dynamic model of learning strategies, which predicts that profit-maximizing banks have incentives to quote non-competing loan rates. In so doing, sensitive borrowers are discouraged to shop around in search of lower loan rates. We further find strong empirical evidence to support the theory from unsecured personal loan rates, while the evidence is weaker in new car loan rates where the competition is at the national level. Finally, we find that the odd pricing (just below integer) is used a device to promote competition in unsecured personal loan rates where there exists substantial level of local market competition.

Bank Loan Rate Clustering: Theory and Evidence

I. Introduction

The question of how to price homogeneous products has received a lot of attention. In this paper, we examine bank loan interest rates. We propose a model where banks take advantage of limited recall by borrowers to tacitly collude at certain focal interest rates. Using data on bank loan rates in more than 130 markets, we test our model against existing models of retail pricing. In specific, we test whether bank loan rates tend to cluster around integer values or values ending in other "even" fractions (such as quarters or tenths of a percent), as our model predicts, or around other rates ("odd" fractions), such as existing models predict.

A walk down a supermarket aisle or a trip to a gasoline station make it obvious that many retail industries find that prices tend to be set just below values ending in "even" fractions. Supermarket and gas prices often end with a 9 (such as $1.99 for cereal or $1.899 for a gallon of gas). One study finds that 80 percent of prices quoted by a major supermarket chain end in a 9 (Wisniewski and Balttberg, 1983). This may be because people have limited recall, and tend to truncate (rather than round) when remembering prices (Brenner and Brenner, 1982).

We ask whether the same phenomenon of "odd" pricing is present in bank loan rates. Bank loan interest rates are like retail prices in that high rates are good for sellers (that is, banks) and banks for consumers (borrowers). Based on evidence from retail markets, we might expect loan interest rates to cluster just below rates ending in even fractions.

Further support for the hypothesis that loan rates should cluster just below rates ending in even fractions is given by Kahn, et. al. (1999), who study bank deposit interest rates. They present and test a model of limited recall that suggests that deposit rates should cluster on values ending in “even” fractions (such as quarters or tenths of a percent). This is because higher deposit rates are more costly for banks, so to take advantage of limited recall, banks should prices at the rates depositors truncate to. Kahn, et. al., find evidence consistent with their model.

We propose an alternative that is consistent with limited recall, but actively models competition among banks. In our model, the way banks compete is affected by the fact that borrowers have limited recall. Our model is related to models of tacit collusion and multimarket contact such as Rotemberg and Saloner (1986) and Berheim and Whinston (1990, 2000).

We provide evidence of loan rate clustering using data on unsecured personal loans and loans for new automobiles. We find that loan rates tend to cluster around rates ending in even fractions, consistent with our theory but not fully consistent with existing models of retail pricing such as earlier models of limited recall. The story is more dynamic, however. There is some pricing below even fractions, and this odd-fraction pricing is more common for auto loans than for personal loans. It is also more common in more concentrated markets. We offer some speculation on why this might occur, but it is the subject of future research.

This paper is organized as follows. In Section II, we develop a model of loan rate clustering and provide some empirical predictions. Section III describes our data and the empirical analysis is presented in Section IV. A conclusion is provided in Section V.

II. A Dynamic Model of Loan Rate Clustering

In this section, we propose a dynamic model of interest rate clustering around integers, and show that this pricing behavior is an optimal strategy for the financial intermediary. Using the principal-agent approach, we posit a financial intermediary as a principal whereas the borrowers as agents. Lenders are succumbed to the information asymmetry regarding the types of borrowers in terms of recall capacity and search cost level. We adopt the physical framework of our model from the dynamic liquidation model by Kahl (2002). The assumptions for the banking agents are similar to ones proposed in Bolton et al. (2004). In their paper, some borrowers are partially uninformed such that they are not able to find financial products, which would fit their needs: namely, naive customers. On the other hand, the sensitive (or sophisticated) customers are well aware of which financial products would fit them in light of the level of loan rate and other financial conditions.

Our definition of naive and sophisticated customers in theorizing "loan" rate clustering is in contrast to the one suggested in the *limited recall model* by Kahn et. al.(1999) for deposit rate clustering. In their study, deposit rate clustering is interpreted as a consequence of banks' exploitation of depositors' limited recall on the decimal points of deposit rates. Their paper presumes bounded rationality on depositors in aggregate so that a bank relies on the exogenously given level of the proportion of depositors in the population when the bank selects the level of deposit rate to maximize profits. Thus, in their definition, "sophisticated" depositors can fully recall a deposit rate (e.g., 2.23) while "naïve" depositors can remember only the integer part of the deposit rate (e.g., 2.00). The limited recall theory on deposit rate clustering by Kahn et al. (1999) predicts that banks tend to set deposit rates at integers and when banks set non-integer rates, they are more likely to be just above, rather than just below, integers. Their empirical evidence supports this prediction. If we simply replicate their work for developing a model of clustering loan rates, we would expect that banks would realize maximum profits when they quote rate just below an integer. Figure 1 gives an example of this relationship between bank profits and lending rates. When there are no naïve borrowers, bank profit smoothly increases in the lending rate until profit is maximized. It then decreases as rates increase above the profit maximizing level. Introducing naïve borrowers changes things because increasing lending rates above an integer rate does not decrease borrowing from these investors. Thus, the bank earns a higher return. The larger the percentage of naïve borrowers, the bigger the distortion. As Figure 1 illustrates, a bank maximizes its return by pricing just below an integer level, much as many retail stores price goods with prices ending in ‘99’.[1] However, one might argue that even a “naïve” customers, when they become borrowers, should become more sophisticated in searching for better loan rate. The fact that the depositors are not sensitive to the third decimal point of a deposit rate may not indicate that they are subject to limited recall. Rather the depositors may not spend the effort to learn the exact deposit rate at their existing bank or to search for a better interest rate unless the expected increase in rate is worth the marginal cost of learning the deposit rate and searching for a new one. Deposit accounts at banks tend to be small relative to loan sizes. It may not be worth the effort to constantly monitor interest rates on a relatively small deposit account. However, it may be worth it to search for a good rate on a relatively large loan.

Our model is based on an idea that a typical agent is more sensitive the change

Regardless of whether depositors are conscious of the decimal of deposit rate or not, the depositors might be prone to be less responsive to the small change of fraction of deposit rate because either of the high search cost or of the other benefits which they had enjoyed. However, as for the borrowers, it would be *absurd* if we maintain the same *limited recall* assumption on the borrowers’ choice, since the borrowers are by nature keen to the level of loan rate unless he is in desperate need for a fund. Thus the current model does not rely on the behavioral

[1] Examination of “just below the round-number pricing” phenomena has been explored in the marketing literature. See Gedenk and Sattler (1999), Schindler and Wiman (1989), and Brenner and Brenner (1982)

assumption such as the shortage of memory capacity as to the borrowers' response to the level of loan rate in explaining the clustering. We demonstrate that the clustering could be an equilibrium outcome on the basis of the optimal response to the other's action.

The time line in Figure 2 provides an overview on the dynamic effects of our model. In this *dynamic* loan rate clustering model, we have two competing banks in a market to maximize profits from borrowers. The financial and physical structure of these two banks' are identical, while their behavior of pricing loan rates may vary. We assume that the two banks divide the customers into two groups at the time 0. Some of them are very sensitive to change in the level of loan interest rate, while others are not. When a borrower shows up before a loan officer at the lending institution, the bank must have *a prior* belief on the probability of borrowers who would maintain the relationship with the bank from the past record of the customers' renewal probability, i.e., client's entrance and exit. The prior probability of sensitive customers is denoted as λ . Notice that λ could reflect the percentage of the sensitive customers in the population. Thus 1-λ denotes the percentage of customers who are not sensitive, *naïve*, to the level of the loan rate.

The naïve customers in our study are assumed to show "loyalty" to one (main) bank although they still care about the general level of interest rate. So the naïve customers in our

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among others for detailed discussions on this issue.

model tend to put more weight on relationship building between them and their main bank, while sensitive borrowers are consistently move around for a lower loan rate. When a borrower take out a loan from the bank at a certain level of interest rate, it does neither necessarily mean that he is satisfied with the terms of the loan contract nor that he is not sensitive to the level of loan rate. Even a highly sensitive customer could not help but borrow a loan in an emergency due to the time constraint despite the higher level of interest rate.[2] Thus the banks are subject to the information asymmetry as to the types of borrowers.

Observing the credit conferring at a given interest rate only gives the bank the imperfect information about the type of borrowers with regard to their sensitivity to the interest rate. In order to retain the borrowers as long lasting customer by responding appropriately to the customer's type, the bank must decide whether to remain ignorant to the customer, *i.e,.* offering the same old level of interest rate for the loan renewal at the time 1 or to take efforts to retain him *i.e,.* either by lowering rate or by conferring benefit at time 1. While the bank wants to adjust *a priori* the term structure of loan for the sensitive customers by the time 1, it never figures out the true type of borrower until he parts with the bank *a posteriori* at time 1. Therefore the bank updates their belief about the type of the customers through the loan renewal process at date 1 using Bayes' rule. Among the customers within the client pool of the bank, the

[2] In the context of buyouts in the banking industry, the interest rate for the *Mezzanine Fund* could fall under the category of this high interest rate case.

probability that the naive customers borrow the loan from the bank's rival is assumed to be zero.[3] The probability that the sensitive customers agree to borrow a loan with the announced rate r_n^0 at date 0 is assumed to be θ_S.[4] Hence the posterior probability that the loan borrowers were originally sensitive at date 1 is given as follows.

$$\Pr(sensitive|borrow) = \phi = \frac{\lambda(1-\theta_S)}{\lambda(1-\theta_S)+(1-\lambda)}. \qquad (1)$$

If the posterior belief about the sensitive customer's portion among the borrowers is fairly optimistic, i.e. low ϕ, the bank may choose to maintain the level of interest rate while ignoring the sensitive customers. The bank's payoff at the date 2 depends not only on the announced interest rate, r_k^t,[5] but also on the posterior belief on the percentage of the sensitive customers among the pool of borrowers, because the *sensitive* borrowers are willing to change the horse.

The bank's lending interest rate at the date 0 is announced as some integer floor or a truncated rate, *i.e.*, r_n^0, which produces a positive spread over the deposit rate. This interest rate r_n^0 is interpreted as the collusive level of rate at the date 0. At the date 1, the bank should reduce the interest rate in response to the rival's loan rate in order to retain the sensitive customers as

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[3] This assumption could be easily relaxed if the size of naive customers within the each own bank's client pool differs from each other, i.e. $\Pr_B(sensitive) = \mu$ whereas $\Pr_A(sensitive) = \lambda$.

[4] The probability θ_S could be interpreted that the sensitive borrowers are in urgent need of money either in order not lose the favorable opportunity or to avoid a temporary delinquency under the fast growing economy.

[5] For r_k^t, '*t*' denotes the date 0 or 1 and *k* denotes the feature of customers: '*s*' for the sensitive customers, '*n*' for the naive

customers, such that $r_s^1 \le r_{Rival}^1$. In response to the bank's adjustment of the rate, the rival bank could also decrease the interest rate so that both banks might engage in *Bertrand* competition, which could lead to the race to the bottom. Thus the bank would like to convey his intention to not start the race to his rival as well as to deter the sensitive customers from looking for a better loan rate. Consequently, in an effort to avoid a downward spiral of interest rate, the banks may choose some integer numbers for the level of lending interest rate, which are easily noticed by others. Hence we could observe the discrete movement of interest rate over time, while clustering loan rate around the integer numbers.

Initially the banks might set up the level of interest rate r_n^0, in order to exploit the naive population since the competing rate from other financing source e.g. stock market, is assumed to be zero. At the date 1, a sensitive borrower will definitely look for a better loan rate unless he is in need of immediate fund. Then, the banks adjust their belief on the portion of sensitive borrowers according to the Bayesian update. Thus the current paper reflects the dynamic feature of loan rate on the proportion of loan borrowers who are sensitive, which is ϕ in equation (1).[6] While maximizing the bank's profit over the loan, each bank should take into account not only the rival bank's response but also the customers' incentive to fly away.

A representative borrower's demand function for a loan is denoted as follows,

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customers, and '*Rival'* for the competing bank.

[6] In Kahn et. al.,(1999), an exogenously arisen proportion of naïve bank depositors κ is adopted. This exogenous feature could be a

$$L = L(r_s^t, r_n^t, r_{rival}^t, x) \tag{2}$$

where r_s^t is the loan rate offered to the visiting customer if he is a sensitive customer, r_n^t for the naïve customers, r_{rival} for the rival bank's loan rate, and x is a vector of other variables. The function L is interpreted as the amount of loan conferred to the borrowers at a point of time. We assume that $r_s^t \leq r_n^t$ for all t. Therefore the expected profit over the loan could be estimated as follows when the bank decides to exploit the naïve customers while they lose the sensitive customers to the rival bank.

$$r_n^1(1-\phi)L(r = r_n^1 \middle| r_{rival} = r_s^1, x) \tag{3}$$

Or as the bank responds to the rival's action, the lending amount changes and loan rate reaches a *Nash* equilibrium.

$$r_s^1 L(r = r_s^1 \middle| r_{rival} = r_s^1, x) \tag{4}$$

Now we develop a specific form of the *loan* demand function as follows for the two competing banks such that

$$L = U - r_i + \phi\, r_{rival}, \quad i = n, s \tag{5}$$

where ϕ denotes the effect of mobility among the sensitive customers on the other bank's demand for loan. Thus, the expected payoff for a bank is derived as follows

$$E(\pi_A) = r_A(U - r_A + \phi\, r_B) \tag{6}$$

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weak point of the paper in light of theoretical robustness.

and

$$E(\pi_B) = r_B(U - r_B + \phi\, r_A) \tag{7}$$

Through a simple calibration of algebra, the Nash equilibrium interest rate r^{nash} is given as follows

$$r_A^{nash} = r_B^{nash} = \frac{U}{2-\phi} \tag{8}$$

If these banks behave as if they were a single bank, the maximized joint profit is realized when the loan rate is

$$r^{\text{joint}} = \frac{U}{2-2\phi} \tag{9}$$

As shown above, the loan rate is decreased to the *nash* equilibrium rate once a bank deviates from the joint profit maximizing loan rate even when U and ϕ are known to each other. In this case, banks are faced with difficulties in maintaining the stable joint-profit maximizing level of loan rates. Furthermore, when the parameters of each bank's loan demand function falls, it would be even harder to retain the optimal level of loan rate. Thus, banks have strong incentives to quote non-competing loan rates such as at whole, quarter, half, and three-quarter of an integer at any level. In so doing, the banks can effectively signal in the loan market that they have no intention to compete with rival banks. Also, this loan pricing behavior will discourage the sensitive loan customers to shop around for a lower loan rate.

In the next two sections, we describe our data and provide some preliminary empirical results which support the predictions in our theory.

III. The Data

The loan rate data in our sample are from the Bank Rate Monitor, Inc (BRM). We obtain weekly 48-month new automobile and 24-month unsecured personal loan rates during the August 16, 1989 to August 8, 1997 sample period.[7] The data are from relatively large 71 commercial banks in 10 large cities: Boston, Chicago, Dallas, Detroit, Houston, Los Angeles, New York, Philadelphia, San Francisco, and Washington D.C. Each week, BRM surveys most Metropolitan Statistical Area (MSA) to collect deposit and consumer lending rates. Since the concept of MSA includes high degree of economic and social integration within a core area together with adjacent communities, it is natural to presume that banks in the identical MSA are competing against each other.

The BRM loan rates are survey data which are based on rates applicable to walk-in customers who has no prior banking relationship with the quoting commercial banks. This feature of BRM loan rates is ideal for us to explore both sensitive borrowers' best rate searching behavior and banks' colluding behavior. Although loan rates can differ from branch to branch, the simple average of the individual branch loan rates are calculated by BRM.

[7] We would like to thank George Pennacchi for allowing the loan rate data used in Kahn et al. (2004).

IV. Empirical Results

The first test in our analysis is to see whether there is any evidence of clustering in the lending rates. We can achieve this goal by simply removing the integer portion of the any loan observations and construct a chart of frequency distribution. We first look at the pattern of loan rate pricing by our sample banks. Figure 3 shows the fraction of quotes at either whole, quarter, half, or three-quarter for unsecured personal loan rates at the individual bank level. We find that more than 60 percent of the sample banks (43 out of 71) have 90 percent of their loan rate quotes ending with either whole, quarter, half, or three-quarter percentage points. This phenomenon of loan rate clustering is significantly different from one observed in Kahn et al. (1999) where limited recall hypothesis can explain the pattern of clustering deposit rates. Consistent with the predictions in our theory, the possibility of collusion is observed from the highly frequent observations in non-competitive prices. The result in Figure 4 for new car loan rates however shows weaker evidence of this pattern. It suggests that the competition car loans markets are more at the national level. Figure 5 for unsecured personal loan rate frequency distribution and Figure 6 for new car loan rate distribution clearly shows that the majority of the portion of lending rate quotes are given at the whole, quarter, half, or at the three-quarter. For the case of new car loan rates in Figure 6, more than 50 percent of bank observations are quoted at the quarter, half, or three-quarter. The limited recall hypothesis would never predict this, while the evidence is consistent with our theory of dynamic loan rate clustering through banks' signaling for non-competition. There is however some evidence of odd pricing (i.e., just below integer) for both Figure 5 and 6.

A natural question arises that what factors are driving this odd pricing in bank lending market. So, we employ several independent variables including market interest rates, banking market variables, and individual bank characteristics variables to explain the asymmetric quotation in loan rates. A market characteristics variable is the Herfindahl-Hirschamn Index (HHI), which measures the level of market concentration in the banking industry. HHI is based on the deposits of commercial bank branches located in each MSA. We obtain the deposits data from the FDIC's Summary of Deposits, which records deposits at the end of June every year. Table 1 shows the results for unsecured personal loan rates. The dependent variables are calculated by dividing just above integer (both 10 basis points and 24 basis points) by sum of just below integer and just above integer. Thus, the value of this variable shows asymmetry in loan pricing. For example, if there is equal number of observations 10 basis points above integer and below integer, we have dependent variable value of 0.5, if all observations are just above integer, we have the value of 1. In Table 1, the coefficients for HHI are negative and statistically significant in four out six cases. This suggests that banks in less concentrated markets (with greater chance for more competition) are more likely to use odd pricing (just below) to promote competition in the loan market. The evidence for this pattern is weaker for new car loan rates in Table 2. None of the HHI coefficients turn out to be significant in the table. The coefficients for merger activity in Table 2 are negative and statistically significant for all three cases in 10 basis points below case.[8] This indicates that more merger activity are likely to make a local market competing banks with greater market power discouraging competition in new car loan markets.

V. Concluding Remarks

The issue of clustering in pricing homogeneous products has received a lot of attention in many fields of academia. In this paper, we examine bank loan interest rates. We propose a model where banks take advantage of limited recall by borrowers to tacitly collude at certain focal interest rates. Using data on bank loan rates in more than 130 markets, we test our model against existing models of retail pricing. In specific, we test whether bank loan rates tend to cluster around integer values or values ending in other "even" fractions (such as quarters or tenths of a percent), as our model predicts, or around other rates ("odd" fractions), such as existing models predict.

Our theory provides a dynamic model of learning strategies, which predicts that profit-

[8] The coefficient is measured by the share of local market deposits in banks involved in mergers in which two or more banks charters are consolidated, averaged over the previous three years.

maximizing banks have incentives to quote non-competing loan rates. In so doing, sensitive borrowers are discouraged to shop around in search of lower loan rates. We further find empirical evidence to support the theory from unsecured personal loan rates, while the evidence is weaker in new car loan rates where the competition is at the national level. Finally, we find that the odd pricing (just below integer) is used a device to promote competition in unsecured personal loan rates where there exists substantial level of local market competition.

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Figure 1. Bank Profits and Lending Rate With Limited Recall Hypothesis

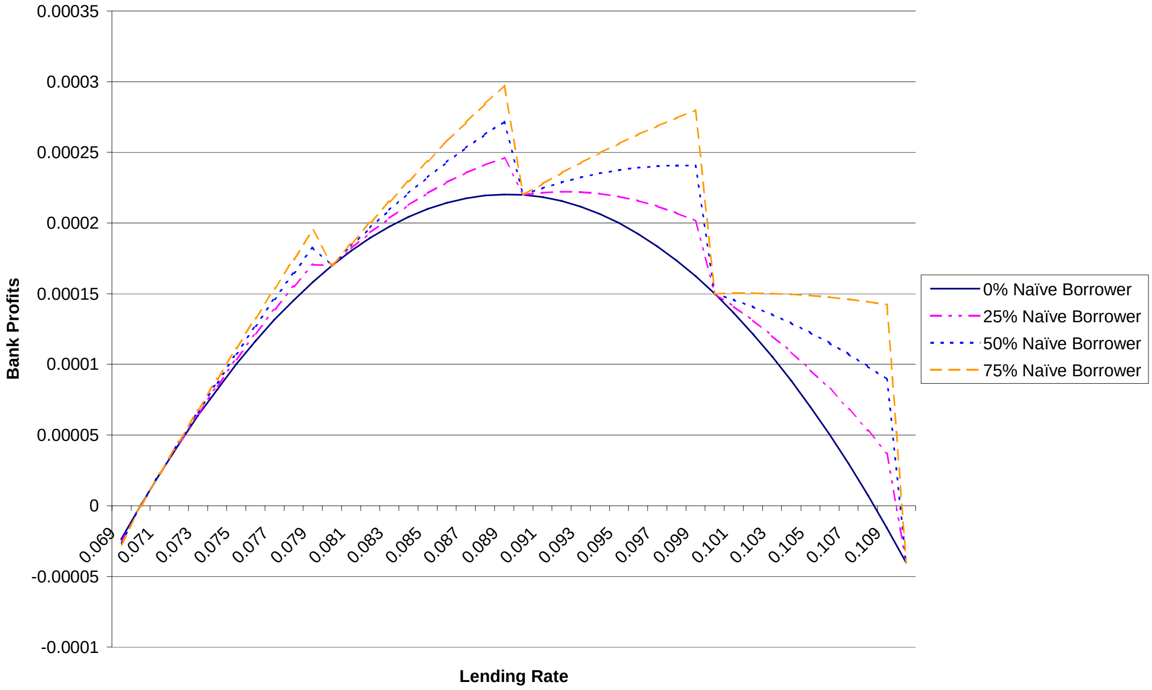

Figure 2. Time Line of the Model with Strategic Loan Rate Pricing

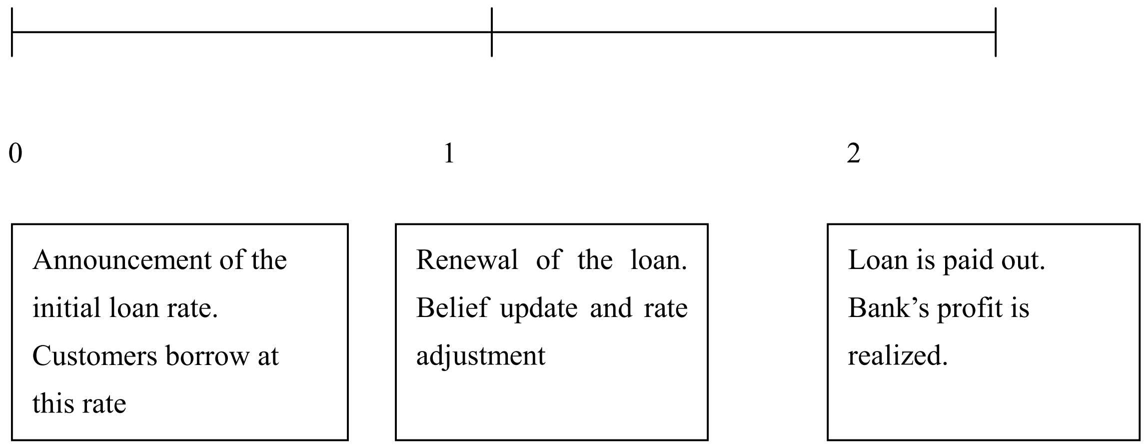

Figure 3. Individual Banks and Their Fraction of Unsecured Personal Loan Rate Set at the Whole, Qtr, Half, or 3-Qtr

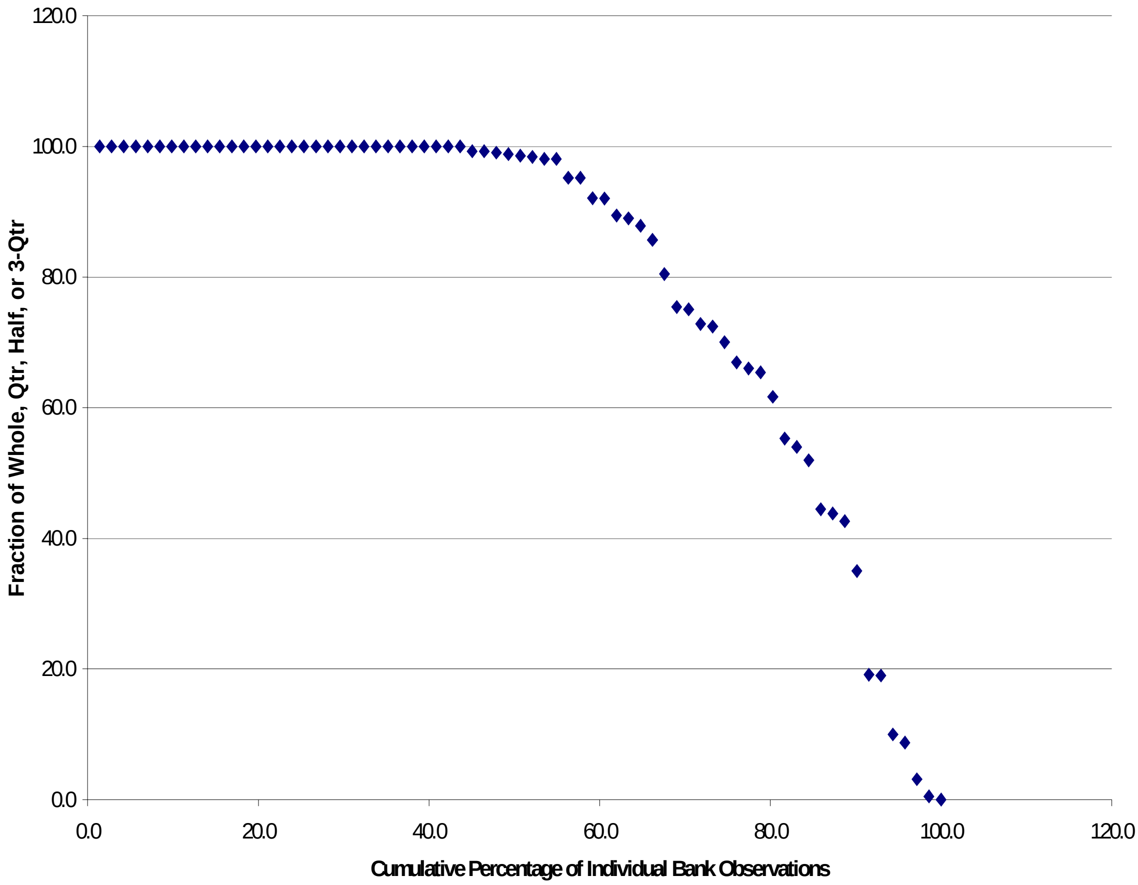

Figure 4. Individual Banks and Their Fraction of New Car Loan Rate Set at the Whole, Qtr, Half, or 3-Qtr

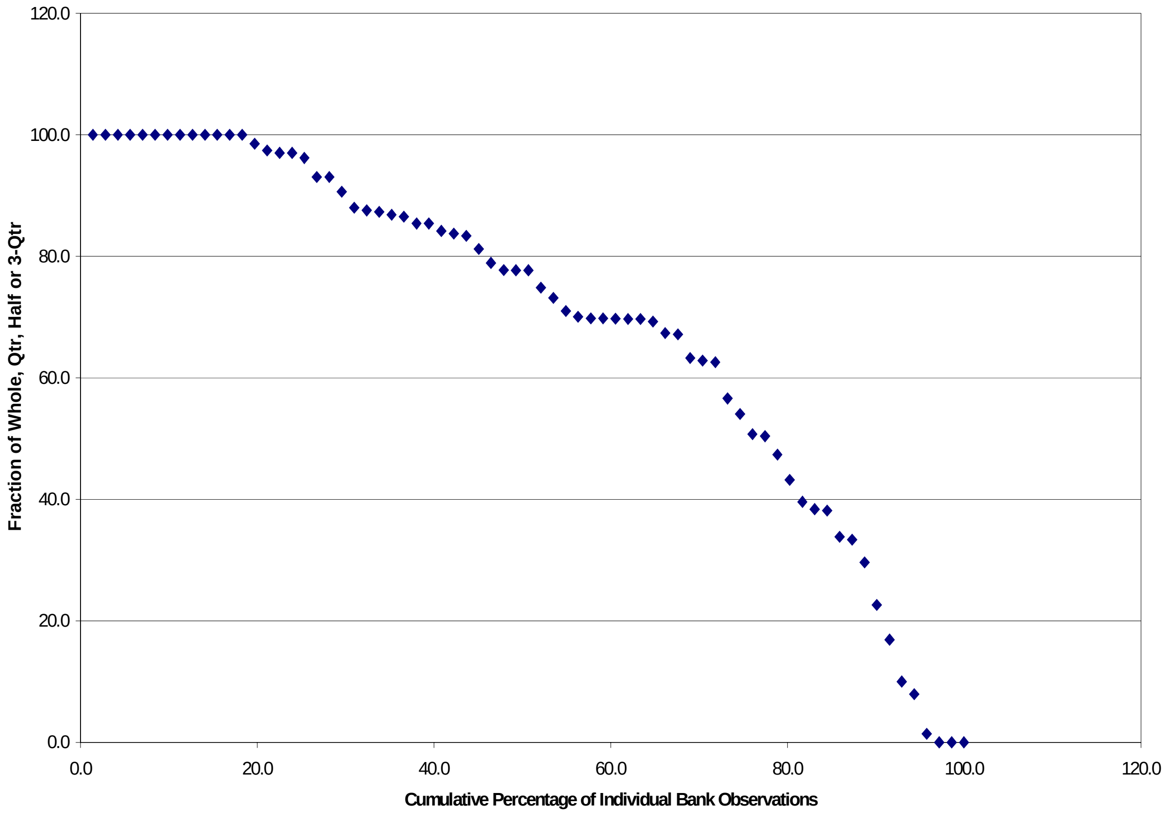

Figure 5. Frequency Distribution of Unsecured Personal Loan Rates

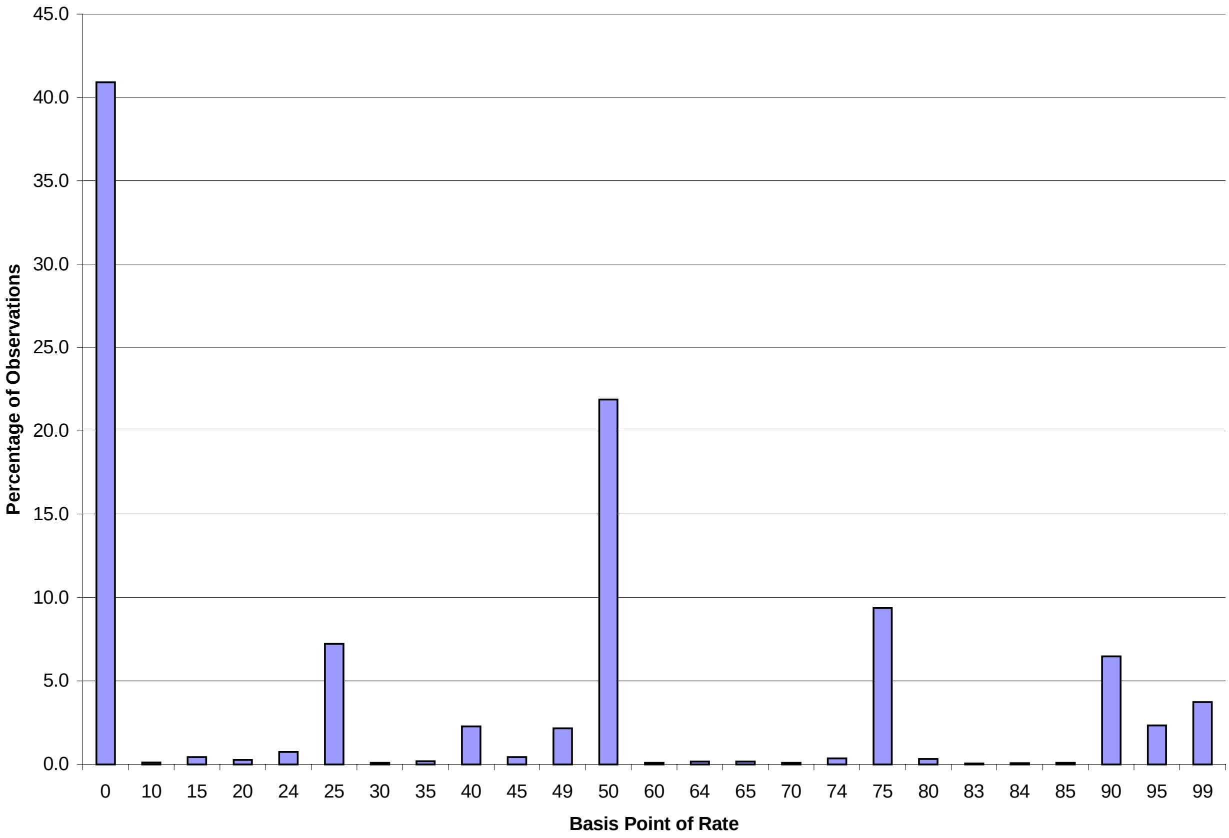

Figure 6. Frequency Distribution of New Car Loan Rates

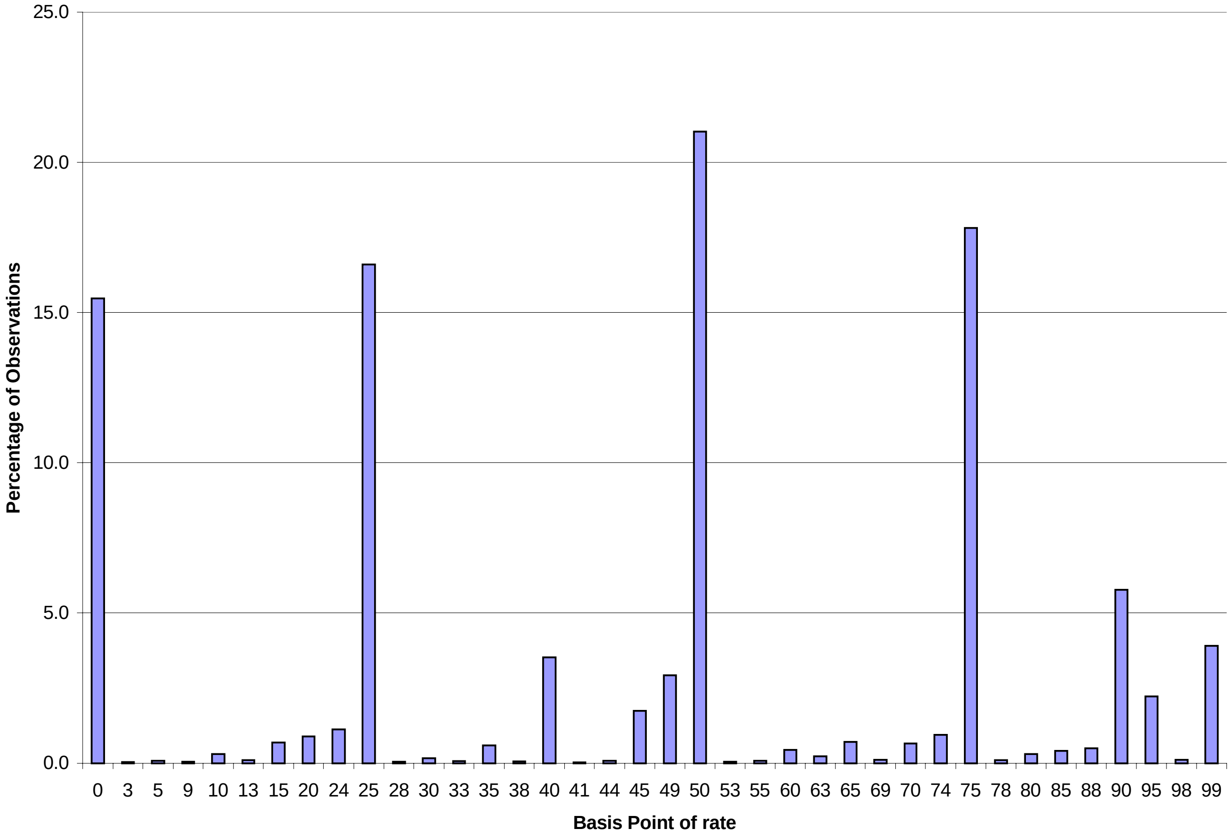

Table 1. Determinants of Asymmetric Unsecured Personal Loan Pricing

	10 BP Below			24 BP Below		
Variable	Coefficients (*t*-statistics in parenthesis)			Coefficients (*t*-statistics in parenthesis)		
Constant	4.454*** (4.04)	1.587*** (2.94)	0.407 (0.15)	3.734*** (3.37)	1.322** (2.32)	0.692 (0.24)
TB1Yr	-0.017 (-0.51)		-0.018 (-0.63)	0.037 (1.10)		0.042 (1.40)
CCR	-0.197*** (-3.50)		-0.104* (-1.76)	-0.167*** (-2.96)		-0.039 (-0.62)
PINC	-0.0009 (-0.28)	-0.001 (-0.33)	0.034** (1.92)	0.0008 (0.23)	0.0007 (0.20)	0.026 (1.39)
POP	-0.106 (-1.62)	-0.133** (-2.07)	-1.547 (-1.14)	-0.026 (-0.39)	-0.035 (-0.51)	-1.733 (-1.20)
HHI	-1.949* (-1.68)	-2.606** (-2.28)	1.031 (0.43)	-2.736** (-2.35)	-2.941** (-2.44)	1.943 (0.77)
AcqAct	0.011 (0.01)	-0.589 (-0.49)	-0.031 (-0.03)	-0.873 (-0.72)	-1.060 (-0.85)	-1.254 (-1.05)
MergAct	-0.312 (-0.89)	-0.446 (-1.30)	-0.160 (-0.49)	-0.707 (0.35)	-0.760** (-2.10)	-0.453 (-1.30)
Year Dummy	No	Yes	No	No	Yes	No
City Dummy	No	No	Yes	No	No	Yes
Observations	90	90	90	90	90	90
R-square	0.177	0.290	0.513	0.163	0.204	0.446

Notes: The dependent variable is the annual average of the loan rate in a particular market for a given year. The sample consists of 10 cities (markets) for the years 1989 to 1997, resulting in 90 observations for each loan type. "TB1Yr" represents the one-year, annually-compounded Treasury bill secondary market yield for the case of personal unsecured loans and is from the Federal Reserve Bank of St. Louis database. "CCR" is the average credit card rate (reported in the Federal Reserve Bulletin) minus the one-year Treasury rate. "HHI" is the Herfindahl-Hirschman Index divided by 1000 computed from end-of-June FDIC Summary of Deposits data of all commercial bank branches within the PMSA. "PINC" is the MSA's per capital income as a percentage of the per capita income of the entire United States. "POP" is the MSA's population as a percentage of the total population of the United States. These data were obtained from the Commerce Department's Bureau of Economic Analysis. "AcqAct" is the share of local market deposits in banks involved in acquisitions in which the banks retain their separate charters but changed their top-tier bank holding company ownership, average over the previous three years. "Year" is a time trend ranging from 1989 to 1997. "MergAct" is the share of local market deposits in banks involved in mergers in which two or more banks charters are consolidated, averaged over the previous three years.

Table 2. Determinants of Asymmetric New Car Loan Pricing

Variable	10 BP Below Coefficients (*t*-statistics in parenthesis)			24 BP Below Coefficients (*t*-statistics in parenthesis)		
Constant	3.090*** (5.25)	1.995*** (3.77)	4.242 (1.61)	1.247** (2.21)	1.160** (2.19)	2.158 (0.78)
TB3Yr	-0.149*** (-2.69)		-0.157*** (-3.24)	-0.012 (-0.23)		-0.023 (-0.45)
FCR	-0.008 (-0.21)		0.023 (0.58)	-0.006 (-0.15)		0.013 (0.30)
PINC	-0.007** (-2.37)	-0.007** (-2.35)	0.003 (0.15)	-0.003 (-1.09)	-0.003 (-1.06)	-0.021 (-1.12)
POP	-0.187*** (-2.99)	-0.179*** (-2.84)	-1.828 (-1.36)	0.006 (0.10)	0.007 (0.11)	0.674 (0.48)
HHI	0.275 (0.25)	0.448 (0.40)	0.907 (0.37)	0.268 (0.25)	0.268 (0.24)	2.351 (0.92)
AcqAct	-1.657 (-1.45)	-1.218 (-1.04)	-1.848 (-1.64)	-1.737 (-1.58)	-1.740 (-1.49)	-1.239 (-1.05)
MergAct	-0.822** (-2.47)	-0.825** (-2.46)	-0.624* (-1.92)	-0.288 (-0.90)	-0.273 (-0.81)	0.095 (0.28)
Year Dummy	No	Yes	No	No	Yes	No
City Dummy	No	No	Yes	No	No	Yes
Observations	90	90	90	90	90	90
R-square	0.296	0.362	0.537	0.069	0.084	0.269

Notes: The dependent variable is the annual average of the loan rate in a particular market for a given year. The sample consists of 10 cities (markets) for the years 1989 to 1997, resulting in 90 observations for each loan type. "TB3Yr" represents the three-year constant maturity Treasury bond rate for the case of new automobile loans and is from the Federal Reserve Bank of St. Louis database. " FCR" is the average yield on new automobile loans charged by the finance company subsidiaries of the three major U.S. automobile manufacturers (taken from the Federal Reserve's Consumer Credit Statistical Release G.19) minus the three-year Treasury rate. "HHI" is the Herfindahl-Hirschman Index divided by 1000 computed from end-of-June FDIC Summary of Deposits data of all commercial bank branches within the PMSA. "PINC" is the MSA's per capital income as a percentage of the per capita income of the entire United States. "POP" is the MSA's population as a percentage of the total population of the United States. These data were obtained from the Commerce Department's Bureau of Economic Analysis. "AcqAct" is the share of local market deposits in banks involved in acquisitions in which the banks retain their separate charters but changed their top-tier bank holding company ownership, average over the previous three years. "Year" is a time trend ranging from 1989 to 1997. "MergAct" is the share of local market deposits in banks involved in mergers in which two or more banks charters are consolidated, averaged over the previous three years.