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# Bank Deposit Rate Clustering: Theory and Empirical Evidence

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**ABSTRACT**

Like security prices, retail deposit interest rates cluster around integers and "even" fractions. However, explanations for security price clustering are incompatible with deposit rate clustering. A theory based on the limited recall of retail depositors is proposed. It predicts that banks tend to set rates at integers and that rates are "sticky" at these levels. The propensity for integer rates increases with the level of wholesale interest rates and deposit market concentration. When banks set non-integer rates, rates are more likely to be just above, rather than just below, integers. The paper finds substantial empirical support for the theory's implications.

RECENT EMPIRICAL RESEARCH HAS DOCUMENTED a widespread tendency for security prices to cluster around integers and "even" fractions of currency units. An example is the decreasing relative frequencies of stock price quotes and transactions made at integer-dollar, half-dollar, quarter-dollar, and eighth-dollar price levels. Standard price theory has difficulty rationalizing such clustering because it depends on the arbitrary choice of the pricing system's unit of account. This has led to new theories which explain even-fraction clustering as an implicit convention that reduces traders' costs of negotiating security prices or as a collusive mechanism for maintaining anticompetitive bid-ask price spreads among security dealers.

This paper reports a similar integer and even-fraction clustering of interest rates on retail bank deposits. Because theories of security price clustering are not applicable to the clustering of deposit interest rates, a new theory based on consumers' limited recall is proposed. In addition to explaining integer clustering, this theory has a number of other consequences. It predicts that noninteger deposit rates should be more frequently observed at rates just above integers rather than just below integers. It also predicts that retail deposit rates are stickier (less likely to change) when rates are quoted as even, rather than odd, fractions. Additional implications are that

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clustering should increase with the level of market interest rates and that both clustering and deposit rate stickiness should be greater in more concentrated (less competitive) bank deposit markets. By analyzing bank deposit rates quoted monthly by more than 600 banks during a $10\frac{1}{2}$ year period, the paper finds substantial empirical support for the theory's predictions. This evidence that clustering and stickiness can result from the limited recall of individuals has more general consequences that should interest economists concerned with price inflexibility and its effects on the misallocation and persistent underemployment of real resources.

There is now a sizeable literature on the clustering of prices. Several studies, including Osborne (1962), Nierderhoffer (1965), Harris (1991), and Christie and Schultz (1994), find that integer-dollar stock prices are more common than half-dollar stock prices, which are more common than quarter-dollar prices, which are more common than eighth-dollar prices. This phenomenon occurs for both stock quotes and transaction prices, and is persistent through time and across different stocks and stock markets. Ball, Torous, and Tschoegl (1985) find a similar clustering in the London gold market's fixing (auction) prices, as do Goodhart and Curcio (1990) in foreign exchange rates. Colwell, Rushing, and Young (1994) show that residential real estate prices tend to cluster on whole thousands and five-hundreds.

In some instances, explicit rules may require that prices cluster at particular fractions, an example being a stock exchange's regulation that allows price quotes at "tick" sizes no smaller than an eighth of a dollar. More interesting, however, are cases where clustering is not mandated, but results from an implicit agreement (custom) among traders. Two main theoretical explanations for such implicit agreements have been proposed in the literature. First, as discussed by Harris (1991) and Ball et al. (1985) and as modeled by Brown, Laux, and Schachter (1991), the custom of clustering on discrete price sets can be a mechanism for reducing the cost of negotiating transactions. By limiting bids and offers to a given set of prices, negotiations can be consummated more rapidly, since negotiators cannot propose frivolous revisions of quotes at minute increments. Limiting quotes to rounded prices can also make recording prices easier, thereby decreasing errors from individuals believing that they have traded at different prices. This implicit agreement can be self-enforcing if professional traders deal with each other on a repeated basis, since noncooperation by an individual could lead to his exclusion from future trading.[1] As an alternative to this negotiation cost hypothesis, Christie and Schultz (1994) and Christie, Harris, and Schultz (1994) propose a second rationale for price clustering. In their view, an agreement to limit price quotes to round fractions may be motivated by the desire

[1] Casual observation is consistent with repeated dealings being an important factor in supporting these implicit agreements. In situations where successive dealings are unlikely, as in the auctioning of unique goods, explicit rules that restrict prices are often enforced. For example, English auctions typically require that new bids exceed a standing bid by a minimum price increment.

to maintain noncompetitive bid-ask spreads. They present evidence that dealers in Nasdaq stocks avoid odd-eighths price quotes in order to maintain quarter-point bid-ask spreads.

If reducing negotiation costs and maintaining noncompetitive bid-ask spreads are the sole causes of clustering, then even-fraction clustering would *not* be pervasive in markets where prices are not negotiated and traders do not make a two-way market (quote both bid and ask prices). Indeed, this appears to be the case in many retail markets where consumer purchases are typically not negotiated and almost always occur at the sellers' quotes. In these nonnegotiated, one-way markets, retailers tend to quote "odd" prices, where an odd price (e.g., \$3.99) is defined as one whose rightmost digits are just below a whole or "even" price (e.g., \$4.00). The unusually high occurrence of odd prices in retail markets, such as department, discount, and grocery stores, is well documented. For example, an analysis of scanner data by Wisniewski and Blattberg (1983) finds that more than 80 percent of prices quoted by a major supermarket chain end with the digit 9. Friedman (1967) and Kashyap (1995) also document this odd-pricing phenomenon.

The absence of negotiations and bid-ask spreads might explain why retail prices are typically not rounded, but the unusually high frequency of odd-pricing in these markets requires its own explanation. The convention of odd-pricing in nonnegotiated retail markets might be linked to the different incentives and a relative lack of information possessed by retail consumers compared to wholesale market traders. Transactions in wholesale markets are typically large, so that minute percentage price differences can have major consequences. Negotiating to obtain the best possible price is a paramount concern for professional traders. In contrast, retail consumers, making smaller transactions, have less incentive to analyze which seller is offering the best possible price. Unlike wholesale traders, who typically have instant access to price quotes from many other traders, retail consumers usually obtain quotes from sellers at different points in time. They receive price information, through advertisements or when shopping, sequentially, but it may not be worth their time and effort to carefully record different sellers' prices. Hence, retail consumers' ability to recall prior price quotes will affect their current buying decisions.

Importantly, experimental tests performed by Schindler and Wiman (1989) find that individuals tend to recall odd-ending prices less accurately than even-ending prices, and that expressing a price as odd-ending increases the likelihood that it will be underestimated when recalled. A biological explanation for this downward bias in recalling odd-ending prices is offered by Brenner and Brenner (1982). They propose a theory of fixed storage capacity which assumes that the extra decision of rounding the initially observed number is costly, so that the cheapest "transfer mechanism" involves simply storing the first digit. Hence, if a price's rightmost digits are not "stored" in memory, odd-ending prices tend to be underestimated. If firms recognize consumers' downward bias in recalling odd-ending prices, they may significantly increase the demand for their products by making odd-ending price quotes rather than slightly higher even-ending ones. Even-ending quotes then represent "pricing points" where product demand experiences a discrete decline. Empirical support for this notion is contained in Blinder (1991). Based on interviews of firm managers, he finds that a majority were reluctant to cross the "psychological barrier" of raising prices from an odd-ending quote to an even-ending one.

Not all firms that market retail products or services quote prices, however. For example, financial institutions customarily quote interest rates (yields), rather than prices, for many of their investments. An intriguing question is whether the retail customers of these financial firms suffer from a similar downward bias when recalling odd-ending yields and, if so, whether these firms exploit this behavior. Financial institutions would profit by quoting retail loan rates with odd-ending yields (so that yields are underestimated when recalled), but, in contrast, by quoting retail deposit rates with even-ending yields (so that yields are not underestimated when recalled).[2] There is some anecdotal evidence that banks may engage in this practice. During 1986–87, Davis, Korobow, and Wenninger (1987) conducted a series of interviews with senior commercial and savings bank officers in the New York City area. They report:

> One banker offered the explanation that as market rates have declined, banks have been reluctant to breach successive single digit "floors" (such as an even 6.00 percent) and have been particularly slow to cut MMDA (Money Market Deposit Account) rates below the old ceiling rate on regular savings deposits even though such cuts might be justified on cost of money grounds. Such a line of argument would suggest that the bankers believe that at least at some critical points, the rate elasticity of demand for MMDAs may be fairly high, so that they fear losing market share by cutting rates at such points. (p. 8)

Although there is an extensive literature analyzing how banks set their retail deposit rates, the possibility that they might exploit the limited recall of their depositors has not been investigated.[3] The goal of this paper is to consider such a possibility. It analyzes a banking firm's optimal strategy for setting deposit rates when some consumers have limited recall but others have full recall. We present a model where the demand for bank deposits by full-recall consumers depends on the bank's actual interest rate (e.g., 3.29 percent), whereas the demand by limited-recall consumers depends on a truncated value of the actual rate (e.g., 3.00 percent). In this environment, we

[2] Note that these implications of limited recall are quite different from those of a theory where banks collude to set anticompetitive rates by restricting them to particular fractions. The limited recall theory predicts systematically different clustering in loan and deposit markets.

[3] Some recent research on deposit-rate-setting behavior includes Diebold and Sharpe (1990), Hannan and Berger (1991), Neumark and Sharpe (1992), and Rosen (1995).

solve for a bank's profit-maximizing deposit rate as a function of its opportunity cost of funds (wholesale-market funding rate) and the proportion of limited recall consumers in its market.

When truncation is assumed to occur at integers, we find that the bank's optimal deposit rate is set either at an integer or at an interior point that satisfies a particular first-order condition. This interior point is more likely to be slightly above rather than slightly below an integer rate, so that the frequencies of noninteger rates above and below integers should be asymmetric. The theory also predicts that the likelihood of a deposit rate being at an integer increases with the level of the wholesale interest rate, the proportion of limited-recall consumers, and the level of concentration in the bank's deposit market. Further, we show that, for a given cost of funds shock, the bank's deposit rate is less likely to change when it is currently at an integer value than when it is not. Thus, deposit rates tend to cluster and are "sticky" at integers, but for an entirely different reason than those given for price clustering in negotiated, two-way financial markets.

One of the attractive features of studying the pricing behavior of a banking firm, as opposed to a nonfinancial firm, is that a relatively accurate measure of changes in "input" or "production" costs is available. Changes in a wholesale funding rate, such as the London Interbank Offer Rate (LIBOR), give a fairly precise measure of changes in a bank's input or opportunity costs. This allows for relatively powerful empirical tests of our theory's predictions. We carry out such tests using monthly money market deposit account (MMDA) and retail certificate of deposit (CD) interest rates for more than 600 individual banks over a $10\frac{1}{2}$ year period. This empirical work confirms the clustering and sticky-integer implications of the model and supports the model's prediction of asymmetry in noninteger frequencies. Further, we present evidence that only small levels of limited recall are needed to generate the integer-clustering and noninteger asymmetries found in the deposit rate data.

The remainder of the paper is organized as follows. Section I describes a model of limited recall and analyzes its theoretical implications regarding bank deposit rates. In Section II, empirical evidence regarding this theory is analyzed. Section III gives conclusions and discusses the broader significance of limited recall in micro- and macroeconomics.

## I. A Model of Deposit Pricing with Limited-Recall Depositors

This section analyzes a bank's optimal deposit rate when some consumers have limited recall. In the spirit of Schindler and Wiman (1989) and Brenner and Brenner (1982), we model limited recall as a process by which a depositor truncates components of a posted deposit interest rate when storing that rate in memory. In practice, the amount of recall, and thus the method of truncation, could differ across depositors. For a deposit interest rate expressed as a percentage yield (e.g., 6.27 percent), some depositors may recall only the integer component (6.00), some may remember up to the first decimal place (6.20), and some may have full recall (6.27). For others, recall may not be in terms of decimal places, but could involve storage of "quarter," "half," and "three-quarter" integer values. It might be easier for a depositor to truncate 6.27 as 6.25, rather than 6.2, because 6.25 is actually stored as 6 and a "quarter." Recollection of a "half," "quarter," or "three-quarter" may be more precise than a decimal, 0.1, 0.2,...,0.9, because the memory "storage space" of the former (half, quarter, and three-quarter being a three-element set) is less than that of the latter (decimals being a nine-element set).

While recognizing that depositor recall may be heterogeneous and complex, our model makes the simplifying assumption that only two extreme types of depositors exist—"sophisticated" depositors with full recall (e.g., 6.27) and "naive" depositors who remember only the integer of the deposit rate (e.g., 6.00). Thus, sophisticated depositors base their decisions on the posted deposit interest rate, denoted by $r_d$, and naive depositors base their decisions on the truncation, or integer floor, of the deposit interest rate, denoted by $[r_d]_-$. Despite this simplification, many of the model's results can be easily recast in terms of alternative truncation methods. The truncated rate, $[r_d]_-$, need not be the integer floor, but could be the floor of the first decimal place or quarter digit. This more general notion of recall is applicable when interpreting our empirical evidence.

Consider the following demand relationship for a particular bank's retail deposits. Let a representative sophisticated depositor's desired holding of a given type of retail deposit at a particular point in time be

$$D = D(r, r_d, x), \tag{1}$$

where $r_d$ is the bank's retail deposit interest rate, $r$ is the market rate on wholesale funds of the same maturity as the retail deposit, and $x$ is a vector of other variables affecting deposit demand. Deposit demand is monotonically increasing in $r_d$.

The relationship for a typical naive depositor is similar, but limited recall implies that his demand depends on the truncated deposit rate:

$$D = D(r, [r_d]_-, x). \tag{2}$$

Notice that the demand in equation (2) is a function of the integer floor of the bank's deposit rate, $[r_d]_-$, and the *actual* level, not the integer floor, of the wholesale market rate, $r$. This specification might appear peculiar, since if a naive depositor has limited recall of the bank's deposit rate she probably has limited recall of all interest rates. However, in the Appendix we show that representative deposit demand functions of the form of equations (1) and (2) can be derived by aggregating the demands of individual depositors who differ in terms of their alternative market-linked investments. In particular, a function in the form of equation (2) can be derived by aggregating the demands of individual naive depositors who have limited recall over all interest rates.[4]

The bank's profits from retail deposits can now be computed. Let $\kappa$ be the proportion of bank depositors who are naive, so that $1 - \kappa$ is the proportion who are sophisticated. Also, let $c$ be the bank's noninterest expense per dollar of deposit. Then if $r$ represents the bank's wholesale funding rate or marginal revenue from investments (LIBOR), its profits from retail deposits are[5]

$$(r - r_d - c)[(1 - \kappa)D(r,r_d,x) + \kappa D(r,[r_d]_-,x)]. \tag{3}$$

The bank's optimal deposit rate can now be determined. We assume that $(r - r_d - c)D(r,r_d,x)$ is a concave function of $r_d$, so that in the absence of naive depositors, the solution to the bank's optimization problem can be characterized by its first-order conditions. Let $r_d^s$ be the value that maximizes $(r - r_d - c)D(r,r_d,x)$; that is, $r_d^s$ would be the optimal deposit rate if the bank faced only sophisticated depositors. Then the following theorem gives the bank's optimal deposit rate when it faces both sophisticated and naive depositors.

THEOREM 1: *When some depositors are naive, the bank's optimal deposit rate $r_d^*$ is in the closed interval $[[r_d^s]_-,[r_d^s]_+]$. If the optimal deposit rate is in the* interior *of this interval then it satisfies the following first-order condition:*

$$r - r_d^* - c = \frac{(1 - \kappa)D(r_d^*) + \kappa D([r_d^s]_-)}{(1 - \kappa)\dfrac{\partial D(r_d^*)}{\partial r_d^*}}. \tag{4}$$

*Proof:* First, consider the case in which the bank is restricted to setting integer-valued deposit rates. In this case, its profits from naive and sophisticated depositors will be equal, since deposit demand for the two groups will be the same. Furthermore, because $(r - r_d - c)D(r,r_d,x)$ is assumed to be concave in $r_d$, profits are also concave when interest rates are restricted to integer values, so that they are highest at either $[r_d^s]_-$ or $[r_d^s]_+$.

[4] In addition to having a reasonable theoretical foundation, the specification in equation (2) simplifies our analysis since changes in the wholesale rate, $r$, do not have discontinuous effects on aggregate deposit demand. Note also that the specifications (1) and (2) imply that the demand of the typical naive depositor is (weakly) less than that of the typical sophisticated depositor, due to the truncation of $r_d$. This is of no significance, as the specifications could be altered to adjust for the average difference. What matters is that the relative demands of the naive and sophisticated depositors vary with a change in the basis points (mantissa) of the quoted deposit rate. This change in relative demands is the essence of limited recall.

[5] Fixed costs of issuing retail deposits (e.g., establishing branch offices) are ignored, but they do not affect the bank's marginal pricing decisions.

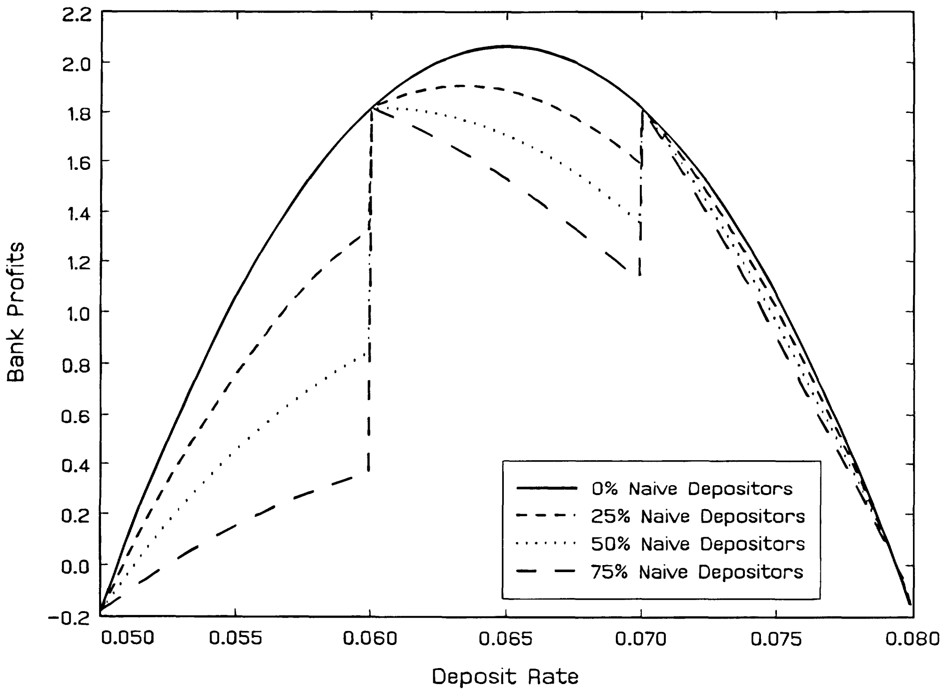


**Figure 1. Bank profit and deposit rate.** A bank's profit as a function of its deposit interest rate is graphed for various proportions of naive depositors in the population. The bank profit function is given by equation (3) with $c = 0.005$ and $D = a_0 + a_1 r + a_2 r_d$, where $a_0 = 0$, and $a_1/a_2 = -0.6$. The market interest rate is assumed to be $r = 8.4375$ percent. In the absence of naive investors, this implies that the profit maximizing deposit rate is $r_d^s = \frac{1}{2}[(1 - a_1/a_2)r - c - a_0/a_2] = 0.8r - 0.0025 = 6.5\%$.

Now consider the general case in which the bank can set a noninteger deposit rate. We can show that as long as $r_d$ is less than $[r_d^s]_-$, profits increase by increasing the interest rate to $[r_d^s]_-$; correspondingly, it can also be shown that if interest rates are above $[r_d^s]_+$, then profits increase by decreasing the interest rate to $[r_d^s]_+$. To demonstrate the first of these claims, note that concavity ensures that since $[r_d^s]_-$ is less than $r_d^s$, profits from the sophisticated depositors increase by bringing the interest rate up to $[r_d^s]_-$. The result for the naive depositors is almost as straightforward. By going through two steps, profits for them can be shown to rise as well. From any initial interest rate $r_d$, bring interest rates down to $[r_d]_-$. This increases profits from naive depositors. Next, increase profits further by moving from $[r_d]_-$ to $[r_d^s]_-$.

Elementary calculations demonstrate that equation (4) is the first-order necessary condition for an interior optimum. Q.E.D.

The effect of including naive depositors is illustrated in Figure 1, which shows a bank's profit as a function of its deposit rate for various proportions of naive depositors in the population. When all depositors are sophisticated

($\kappa = 0$), as indicated by the solid line, profits are a smooth function of the offered deposit rate, and the profit-maximizing rate is $r_d^s = 6.5$ percent. In contrast, when three-quarters of depositors are naive ($\kappa = 0.75$), as indicated by the long dashed line, bank profits increase dramatically as the interest rate moves from, say, 5.9 percent to 6.0 percent, as this brings in a large number of new deposits. From that point, small increases in interest rates decrease profits, until the next breakpoint is achieved. Thus, the profitable thing to do when most depositors are naive is to set the deposit rate at a breakpoint.

When many, but not all, depositors are sophisticated, it may be optimal to choose an interior deposit rate, although this rate is not the same as the optimal rate that would be set when all depositors are sophisticated. Figure 1 gives an example of this for the case in which naive depositors make up one-quarter ($\kappa = 0.25$) of all depositors. As indicated by the short dashed line, the profit-maximizing interest rate is at the interior rate of 6.34375 percent.

As Figure 1 illustrates, because demands by naive depositors are a discontinuous function of $r_d$, the bank's profit function is also discontinuous. The result is that the optimal deposit rate can either be an endpoint of the interval described in Theorem 1 or an interior point satisfying the conditions of equation (4). Any point satisfying equation (4) is less than $r_d^s$.[6] The solution to equation (4) may even lie below $[r_d^s]_-$, in which case the profit maximizing rate is always at one of the endpoints of the interval. Thus, if the optimal deposit rate is interior, it is in the range $[r_d^s]_-$ to $r_d^s$, suggesting that deposit rates at or just above integer values are more common than deposit rates just below integer values.

The interpretation of equation (4) is that the optimal deposit rate balances the benefit of increasing the interest rate spread with the cost of losing deposit market share. The more naive depositors there are, the lower the cost to market share of a small decrease in the deposit rate. Thus, as long as the choice is interior to the interval, the deposit rate declines from $r_d^s$ with increases in the proportion of naive individuals. Eventually, of course, the number of naive depositors becomes great enough that the optimum is an endpoint (integer deposit rate)—the solution moves to the endpoint having relatively higher profits and remains there for further increases in the proportion of naive individuals. The move may be to the integer floor *or* the integer ceiling of the interval. In Figure 1, we choose a borderline example, so that profits are the same at either endpoint.

Theorem 1 gives us a direct means for calculating the optimum. We begin by taking the optimum in the absence of naive individuals and use it to find the interval endpoints. We then compute the bank's profits at the interior point satisfying the first-order condition (4), if such an interior point exists.

[6] This can be seen by differentiating equation (4) and using the first- and second-order conditions for an optimum to show that when $(1 + \kappa)D([r_d^s]_-) > \kappa D(r_d^*)$, then $\partial r_d^*/\partial\kappa < 0$. The condition $(1 + \kappa)D([r_d^s]_-) > \kappa D(r_d^*)$ always holds at $\kappa = 0$, which is where $r_d^* = r_d^s$. Thus $r_d^* < r_d^s$ for $\kappa > 0$. We thank a referee for pointing this out.

The optimum is at this point or one of the two endpoints, whichever gives the highest profits. Figure 2, Panel A plots the optimal deposit rate as a function of the bank's wholesale market rate, $r$, assuming a linear demand schedule and naive individuals being one-half of the population ($\kappa = 50$ percent). Notice that when the wholesale market rate is low, the optimal deposit rate is almost always an interior maximum, making it a continuous function of the market rate. At intermediate market rates, the optimal deposit rate is interior at points just above integer values, after which it then jumps to the next integer. At high market rates, there are no interior maxima, and the optimal deposit rate jumps between integers. Intuitively, only when the market rate is sufficiently low is the incremental profit from sophisticated depositors' increased demand large enough to outweigh the marginal cost of raising the quoted deposit rate within integer values.

Thus, as is illustrated in Figure 2, Panel A, the likelihood of the bank setting its retail deposit rate at an integer should increase with increases in wholesale rates. Furthermore, once the quoted interest rate is at an integer, the likelihood of the bank changing its deposit rate decreases for any given change in the market rate. In other words, deposit rates are *stickier* when they are currently at an integer value. Previous empirical work, such as Hannan and Berger (1991), finds greater deposit rate stickiness in more concentrated bank deposit markets. If stickiness is at least partially due to banks' tendency to maintain integer-valued deposit rates, then an interesting question is whether this tendency, and hence deposit rate stickiness, increases with market concentration.

The following corollary confirms that the likelihood of the bank's setting its retail deposit rate at an integer increases with increases in the wholesale rate and suggests that a decline in competition does, indeed, lead to greater stickiness.

COROLLARY 1: *Suppose $\kappa > 0$ and deposit demand is of the linear form $D = a_0 + a_1 r + a_2 r_d$, with $a_2 > 0$ and $|a_1| < a_2$.*

a. *For a sufficiently high wholesale market interest rate, r, the optimum is always at one of the endpoints of the interval described in Theorem 1.*
b. *For a sufficiently high value of $a_0$, the optimum is always at one of the endpoints of the interval described in Theorem 1.*

*Proof:* (a) Noting that $r_d^s = \frac{1}{2}[(1 - a_1/a_2)r - c - a_0/a_2]$ and using condition (4) for the case of linear demand, we obtain

$$r_d^* - [r_d^s]_- = \chi - \left(\frac{a_1 + a_2}{4a_2}\right)\frac{\kappa}{1-\kappa} r + \frac{1 - \frac{1}{2}\kappa}{1-\kappa}(r_d^s - [r_d^s]_-), \tag{5}$$

where

$$\chi \equiv -\tfrac{1}{2}\left[\frac{c}{a_2} + \frac{a_0}{a_2(1-\kappa)}\right] + \tfrac{1}{4}\left(c + \frac{a_0}{a_2}\right)\left[\frac{a_2(1-\kappa) - a_1}{a_2(1-\kappa)} + \frac{\kappa}{1-\kappa}\left(\frac{a_2 + a_1}{a_2 - a_1}\right)\right]. \tag{6}$$

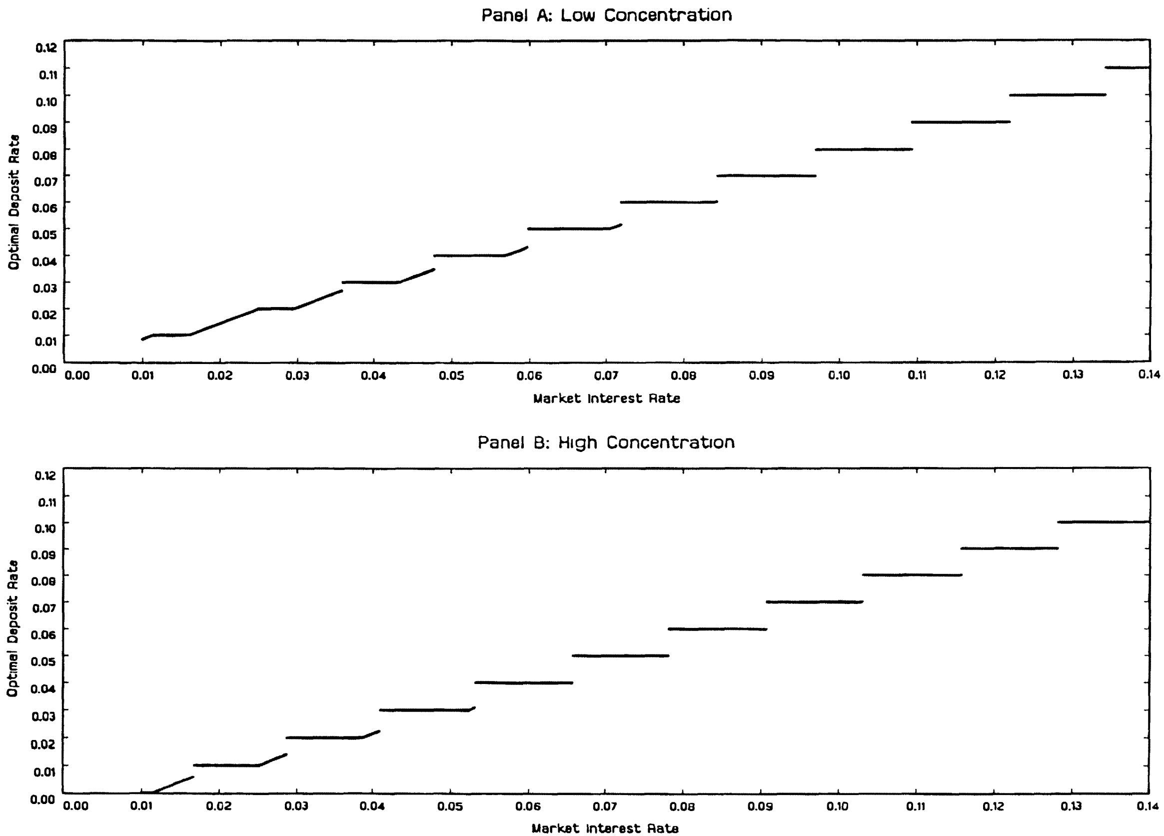


**Figure 2. Optimal bank deposit rates.** A bank's optimal deposit rate as a function of the wholesale market interest rate is graphed. The bank's profit function is given by equation (3) with the proportion of naïve depositors, $\kappa$, assumed to equal 50 percent, $c = 0.005$, and $D = a_0 + a_1 r + a_2 r_d$, where $a_1/a_2 = -0.6$. Panel A, reflecting a bank deposit market with low concentration, assumes $a_0/a_2 = 0$. Panel B, reflecting a bank deposit market with high concentration, assumes $a_0/a_2 = 0.01$.

The left-hand side of equation (5), $r_d^* - [r_d^s]_-$, is the difference between the deposit rate satisfying condition (4) and the lower endpoint. It is an increasing function of $r_d^s - [r_d^s]_-$, the deposit rate optimum in the absence of naive depositors relative to its floor. However, since $a_2 > 0$ and $|a_1| < a_2$, $r_d^* - [r_d^s]_-$ is a decreasing function of the wholesale market interest rate, $r$. Thus, $r_d^* - [r_d^s]_-$ shrinks with increases in $r$ and eventually becomes negative, meaning that an interior point satisfying condition (4) no longer exists and that the optimum is always at one of the endpoints.

(b) For $|a_1| \leq a_2$, $\chi$ in equation (6) is a decreasing function of $a_0$. Therefore $r_d^* - [r_d^s]_-$ becomes negative for sufficiently large $a_0$, and an interior point no longer exists. Q.E.D.

The assumption is that $|a_1| < a_2$ is necessary for the equilibrium spread between wholesale market rates and retail deposit to widen as market rates rise. Theoretical and empirical evidence support this implication, and if the opposite inequality held, it would imply that $r_d^s$ would exceed $r$ for sufficiently high wholesale market rates.[7]

An increase in $a_0$, which shifts up the individual bank's deposit demand curve, is a straightforward way of characterizing a decline in competition. To see this, note that the equilibrium deposit rate in the absence of naive depositors, $r_d^s = \frac{1}{2}[(1 - a_1/a_2)r - c - a_0/a_2]$, is decreasing in $a_0$. Thus, the spread, $r - r_d^s - c$, and bank profits increase as $a_0$ increases. Theories of spatial competition where concentration is directly modeled produce the same type of shift.[8] This aspect of Corollary 1 is illustrated by comparing Panels A and B of Figure 2, whose parametric assumptions are the same except that $a_0/a_2 = 0.01$ in Panel B whereas $a_0/a_2 = 0$ in Panel A. Clearly, the tendency to set integer-valued deposit rates is greater when competition is less (Panel B). Thus, because banks have a greater tendency to maintain integer deposit rates, our model provides an explanation for the empirical link between concentration and deposit rate stickiness.

## II. Empirical Evidence

### A. Data Description and Evidence of Clustering

To test the implications of the model presented in the previous section, we obtain data on bank deposit rates from the Federal Reserve System's *Survey of Selected Deposits and Other Accounts*. This data set contains retail deposit rates quoted by individual banks during the week ending on the last Wednes-

[7] See Hutchison (1995), Hannan and Liang (1991), and Hutchison and Pennacchi (1996).

[8] Consider the circular city model of Salop (1979) where $N$ banks are uniformly distributed on a circle of circumference $S$. In this model, an individual bank's deposit demand is given by $D = r_d - r_c - S/N$, where $r_c$ is the rate offered by the bank's competitors. If $r$ is the marginal revenue from investments and $c$ is the noninterest cost per dollar of deposits, then the equilibrium deposit rate is $r_d^s = r - c - S/N$. As in the linear demand curve assumed in the text, an increase in concentration (reduction in $N$) shifts up the individual bank's demand curve and increases the spread $r - r_d^s - c = S/N$.

**Table I**

**Deposit Interest Rate Summary Statistics**

The sample is from the Federal Reserve System's *Survey of Selected Deposits and Other Accounts* over the period November 1983 to May 1994. This data set contains retail deposit rates quoted by individual banks during the week ending on the last Wednesday of each month. MMDA, CD3, CD6, and CD12 denote the money market deposit account rate, and 3-, 6-, and 12-month certificate of deposit rates, respectively. The mean spread is the average difference between the percentage LIBOR and the deposit rate. One-month LIBOR is used for MMDAs, three-month LIBOR for CD3s, six-month LIBOR for CD6s, and 12-month LIBOR for CD12s.

| Deposit | Mean Rate | Min. Rate | Max. Rate | Std. Dev. Rate | Mean Spread | Total Observations | Number of Banks |
|---|---|---|---|---|---|---|---|
| MMDA | 6.22 | 1.70 | 11.50 | 1.51 | 1.78 | 42,187 | 643 |
| CD3 | 6.53 | 1.65 | 11.50 | 1.75 | 1.30 | 48,971 | 662 |
| CD6 | 6.94 | 2.00 | 12.50 | 1.81 | 1.03 | 50,317 | 662 |
| CD12 | 7.11 | 2.00 | 12.50 | 1.83 | 1.07 | 49,883 | 662 |

day of each month. Summary statistics are given in Table I. Our sample period extends from November 1983 to May 1994 and contains 42,187 observations of MMDA rates, 48,971 observations of three-month CD (CD3) rates, 50,317 observations of six-month CD (CD6) rates, and 49,883 observations of 12-month CD (CD12) rates.[9]

The CD rates in this survey are for small-denomination (less than $100,000) retail CDs. However, investor balances held in retail CDs are generally larger than those of MMDAs, and the potential investor market for these CDs typically exceeds that of MMDAs. For most banks, MMDAs are marketed only in the bank's local region, whereas CDs may be marketed to investors nationwide through CD brokers.[10] Facing only local competition, banks may have more market power in setting MMDA rates, and, indeed, Table I shows that the average LIBOR–MMDA rate spread is significantly greater than any of the LIBOR–CD rate spreads. Furthermore, the local market for MMDAs suggests that the proportion of naive investors should be relatively greater for MMDAs than for CDs.[11]

Figure 3 gives the actual frequency distribution of the mantissas of MMDA interest rates. The histogram shows the percentage of observations at each basis point. The basis points are labeled from 00 to 99, where, for example,

[9] Each deposit rate series represents quotes from over 600 different banks, though due to mergers, acquisitions, and failures, not all banks reported rates for the entire sample period.

[10] Berger and Hannan (1989) find significantly lower rates paid on MMDAs, CD3s, and CD6s by banks in more concentrated local markets, though the link is strongest for MMDAs. No such relationship is found for CD12s. Furthermore, Jackson (1992) compares MMDA and CD6 rates across local markets and finds that the pricing of CD6s is national in scope but the pricing of MMDAs is more locally determined.

[11] MMDAs can be withdrawn on demand and typically require lower minimum account balances than CDs. These features make MMDAs more attractive to less sophisticated, lower wealth investors.

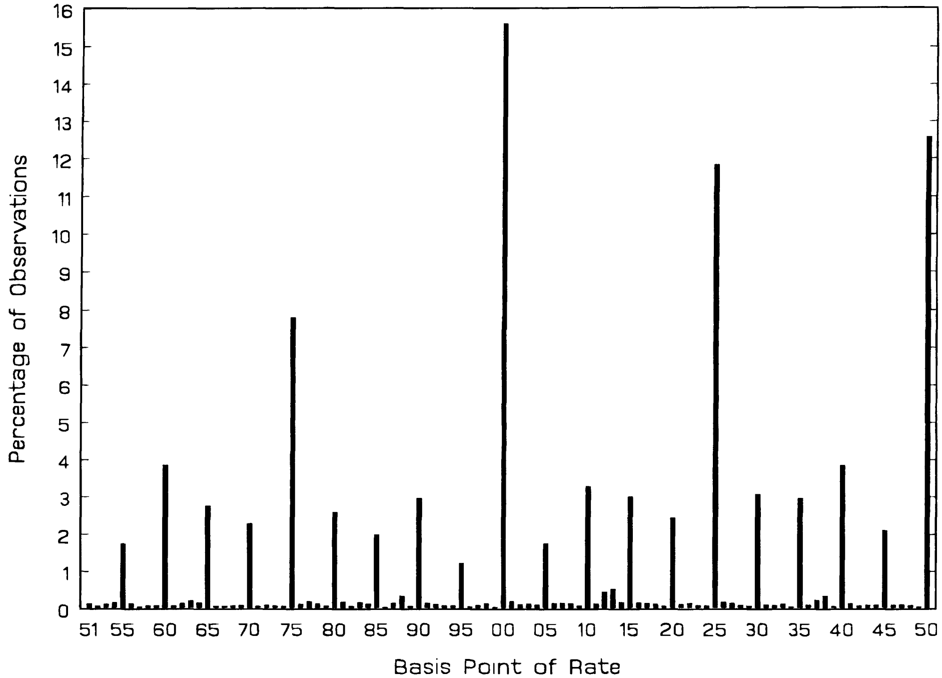


**Figure 3. Distribution of MMDA rates.** The figure is a histogram of the mantissas (basis points) of money market deposit account (MMDA) percentage interest rates. The 42,187 observations are from the period November 1983 to May 1994 and are taken from the Federal Reserve System's *Survey of Selected Deposits and Other Accounts*.

00 refers to an integer percentage deposit rate and 50 refers to a deposit rate set at a half of a percent. The histogram is centered on the integer deposit rate to highlight its potential asymmetry around this point. Though not presented here, histograms for each of the different maturity CDs are very similar. Consistent with the previous section's model, we find that the single most common rate is one set at an integer: 15.6 percent of MMDA, 13.0 percent of CD3, 11.4 percent of CD6, and 13.9 percent of CD12 observations. In addition, there are "spikes" in the frequency distribution at the half-, quarter-, and three-quarter-integer levels, and to a lesser extent, at every five basis points. For example, 48.3 percent of MMDA, 45.4 percent of CD3, 40.5 percent of CD6, and 41.7 percent of CD12 observations are rates set at either the whole, half, quarter, or three-quarter integer. This suggests that limited recall may extend beyond our model's assumption that truncation occurs only at the integer of the deposit rate. Some depositors at particular banks may recall quarter-integer rates. A straightforward generalization of the model would explain the existence of *secondary* pricing points at half, quarter, and three-quarter integers in addition to the *primary* pricing point of the integer of the deposit rate.

### *B. Evidence of Asymmetry in the Frequency of Noninteger Deposit Rates*

In addition to clustering, another implication of our basic model is that when a bank sets a noninteger rate, this rate is more likely to be just above an integer rather than just below an integer. Evidence that is consistent with this predicted asymmetry is that for each type of deposit in our sample, the percentage rate mantissa of 95 is the single *least* common of the 20 possible five-basis point mantissas {00,05,10,...,95}. We also investigate the presence of more general asymmetry by comparing the frequencies of deposit rate mantissas in the below-integer range of 51 to 99 basis points versus the above-integer range of 1 to 49 basis points.[12] The percentage of observations in the above-integer range of 1 to 49 basis points is reported in Table II, Panel A, for each deposit type and for each integer rate appearing in our sample. For example, the table shows that 11.0 percent of all MMDA rates, excluding whole and half-integers, are 49 basis points above or below the integer 8—that is, they are within the ranges 7.51 to 7.99 and 8.01 to 8.49. Of these rates which surround the integer 8, 60.3 percent are above the integer. A goodness-of-fit test of the null hypothesis that rates surrounding the integer 8 are uniformly distributed has a chi-squared test statistic of 142.1, indicating a rejection at the 1 percent significance level.

Evidence of general asymmetry in the distribution of deposit rates is inconclusive when one analyzes the data solely on an integer-by-integer basis. Table II, Panel A, shows that there is wide variation across different integers in the percentages of rates in the above-integer range. This variation should not be too surprising because our sample's retail deposit rates are generated by movements in wholesale market interest rates, such as LIBOR. If wholesale rates during our sample period are not uniformly distributed around each individual integer, neither would one expect uniformity at each integer for deposit rates, even in the absence of limited-recall behavior. However, the null hypothesis of uniformity above and below integers should be more reasonable for both wholesale and (in the absence of limited recall) retail deposit rates if one aggregates observations for all integers.

To evaluate the validity of a null hypothesis of uniformity when aggregating over all integers, we generate samples of "predicted" deposit rates for each deposit type. This is done by first estimating the linear regression $r_{dit} = \alpha_0 + \alpha_1 r_t + \epsilon_{it}$ for each deposit type, where $r_{dit}$ is the actual deposit rate of bank $i$ at date $t$ and $r_t$ is the equivalent maturity LIBOR at date $t$.[13]

[12] This comparison excludes the half-integer deposit rate of 50 basis points which is the exact midpoint of noninteger rates. However, it includes the quarter-integer rates of 25 and 75 basis points, where clustering clearly occurs. Including these rates does not bias a test of the model's asymmetry hypothesis since equal clustering at quarter-integers would be expected in the absence of this hypothesis. Retaining these quarter-integer rates provides for a more powerful test.

[13] Recall that if deposit demand is a linear function of the deposit and market rates, then, in the absence of naïve depositors, the equilibrium deposit rate is a linear function of the market rate.

## Table II

## The Distribution of Deposit Interest Rates above and below an Integer

This sample of retail deposit interest rates is from the Federal Reserve System's *Survey of Selected Deposits and Other Accounts* over the period November 1983 to May 1994. MMDA, CD3, CD6, and CD12 denote the money market deposit account rate, and 3-, 6-, and 12-month certificate of deposit rates, respectively. In Panel A, the sample includes all observations except those at the exact whole and half integer. The total numbers of observations are 30,296, 36,825, 39,230, and 37,804 for MMDAs, CD3s, CD6s, and CD12s, respectively. In Panel B, the sample includes all observations in the 1 to 24 and 76 to 99 basis point ranges. The total numbers of observations are 10,559 13,259, 14,341, 14,226 for MMDAs, CD3s, CD6s, and CD12s, respectively. In Panel A (Panel B), Obs. (%) is the percentage of total observations 49 (24) basis points below and 49 (24) basis points above the indicated integer. Above (%) is the percentage of observations in the 49 (24) basis point range above the integer relative to the observations both 49 (24) basis points below and above the integer. G of F test is the goodness of fit test statistic of the hypothesis that the distribution of observations in the above-integer range versus the below-integer range exceeds that predicted by the uniform distribution.

| | MMDA | | | CD3 | | | CD6 | | | CD12 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Integer | Obs. (%) | Above (%) | G of F Test* | Obs. (%) | Above (%) | G of F Test* | Obs. (%) | Above (%) | G of F Test* | Obs. (%) | Above (%) | G of F Test* |
| Panel A: The Distribution of Deposit Rates 49 Basis Points above and below an Integer | | | | | | | | | | | | |
| 2 | 1.6 | 90.5 | 324.9* | 1.5 | 97.9 | 513.0* | 0.7 | 100.0 | 291.0* | 0.2 | 100.0 | 86.0* |
| 3 | 3.6 | 40.9 | | 6.9 | 35.6 | | 7.2 | 51.2 | 1.7 | 6.5 | 69.4 | 367.7* |
| 4 | 1.9 | 45.1 | | 2.4 | 35.0 | | 2.7 | 31.6 | | 4.4 | 37.1 | |
| 5 | 31.9 | 86.5 | 5149.0* | 12.9 | 88.4 | 2803.3* | 5.9 | 86.9 | 1268.9* | 3.3 | 77.5 | 370.7* |
| 6 | 26.0 | 36.5 | | 24.8 | 42.5 | | 21.1 | 52.7 | 23.7* | 18.2 | 56.6 | 118.5* |
| 7 | 13.7 | 34.4 | | 25.3 | 56.8 | 172.5* | 25.2 | 61.5 | 520.9* | 23.6 | 57.8 | 216.5* |
| 8 | 11.0 | 60.3 | 142.1* | 13.8 | 38.8 | | 20.6 | 34.1 | | 26.2 | 33.7 | |
| 9 | 8.8 | 36.6 | | 8.0 | 39.2 | | 9.1 | 50.1 | 0.0 | 8.9 | 50.0 | 0.0 |
| 10 | 1.3 | 27.0 | | 3.8 | 32.4 | | 5.3 | 46.2 | | 5.5 | 40.6 | |
| 11 | 0.1 | 15.4 | | 0.5 | 20.6 | | 2.0 | 15.7 | | 3.0 | 29.5 | |
| 12 | | | | | | | 0.1 | 3.4 | | 0.3 | 38.1 | |
| All | 100.0 | 55.83 | 411.3* | 100.0 | 50.95 | 13.3* | 100.0 | 51.43 | 32.0* | 100.0 | 49.20 | |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel B: The Distribution of Deposit Rates 24 Basis Points above and below an Integer | | | | | | | | | | | | |
| 2 | 0.8 | 71.9 | 17.1* | 0.7 | 96.6 | 77.4* | 0.2 | 100.0 | 31.0* | 0.1 | 100.0 | 18.0* |
| 3 | 5.0 | 38.5 | | 8.0 | 37.5 | | 10.2 | 49.9 | | 8.9 | 62.2 | 75.4* |
| 4 | 2.6 | 46.9 | | 2.1 | 36.7 | | 2.8 | 41.2 | | 4.8 | 43.5 | |
| 5 | 30.6 | 78.5 | 1052.9* | 10.8 | 79.1 | 485.7* | 4.2 | 79.6 | 213.2* | 2.3 | 70.2 | 52.5* |
| 6 | 24.1 | 45.3 | | 22.8 | 51.7 | 3.6 | 22.3 | 53.4 | 14.7* | 19.6 | 55.0 | 27.9* |
| 7 | 16.0 | 37.8 | | 29.7 | 58.5 | 114.0* | 25.5 | 58.6 | 108.5* | 22.1 | 53.8 | 18.5* |
| 8 | 10.4 | 55.4 | 12.9* | 13.4 | 44.6 | | 19.5 | 41.2 | | 26.5 | 41.2 | |
| 9 | 9.3 | 44.9 | | 8.2 | 38.9 | | 9.1 | 56.3 | 20.7* | 8.3 | 55.9 | 16.4* |
| 10 | 1.2 | 37.0 | | 3.8 | 31.3 | | 4.7 | 48.4 | | 4.8 | 45.1 | |
| 11 | 0.0 | 100.0 | 3.0 | 0.4 | 48.2 | | 1.4 | 22.8 | | 2.6 | 38.7 | |
| 12 | | | | | | | 0.0 | 0.0 | | 0.1 | 11.8 | |
| All | 100.0 | 55.13 | 111.1* | 100.0 | 52.74 | 39.9* | 100.0 | 52.44 | 34.3* | 100.0 | 50.71 | 2.87 |

A single asterisk indicates rejection of a uniform distribution hypothesis at the one percent level, $\chi^2\ (1)|_{1\%} = 6.63$.

Based on the parameter estimates and the actual frequency of LIBORs found in our sample, we then generate samples of predicted deposit rates equal to $\hat{r}_{dit} \equiv \hat{\alpha}_0 + \hat{\alpha}_1 r_t + \eta_{it}$ where $\eta_{it} \sim N(0, \hat{\sigma}_\epsilon^2)$ is simulated 1000 times per actual sample observation using a random number generator. Comparing these predicted deposit rates' frequencies 50 basis points above and 50 basis points below the integer, we find that the percentages of rates above the integer were 50.012, 49.985, 50.012, and 50.002 for the MMDA, CD3, CD6, and CD12, respectively.

Since the frequencies of deposit rates predicted by the distributions of LIBORs in our sample are nearly uniform above and below integers, a null hypothesis of uniformity appears valid when testing for excess asymmetry in our sample aggregated over all integers. The last row in Table II, Panel A, reports the results of such a test. It shows the actual frequencies of all noninteger deposit rates in the above-integer 1 to 49 basis point range versus the below-integer 51 to 99 basis point range. For three of the four deposit types (the only exception being the CD12), more noninteger observations are just above the integer than just below the integer. Additionally, a goodness-of-fit test for these three deposit types rejects the hypothesis of uniformity in favor of a greater above-integer frequency at the 1 percent significance level.

As a check for robustness, we also calculate frequencies of noninteger deposit rates over the shorter ranges of 76 to 99 basis points versus 1 to 24 basis points. The results are reported in Table II, Panel B, and are similar to those for the longer ranges. As before, the percentages of rates above the integer vary significantly when compared across different individual integers. However, aggregating these observations over all integers indicates greater above-integer frequencies for all four deposit types. Goodness-of-fit tests of the null hypothesis of a uniform distribution can be rejected at the 1 percent significance level for all deposit types except for the CD12.[14] In summary, this empirical evidence provides general support for the model's prediction of asymmetry in the distribution of noninteger rates.

### *C. Evidence of the Relative Stickiness of Integer Deposit Rates*

As predicted by Theorem 1 and as illustrated in Figure 2, a bank's propensity to change its deposit rate should be less sensitive to a given shock in its wholesale market funding rate when the deposit rate is currently at an integer value. In this section, we investigate whether the data support this notion of relative stickiness at integer values. In testing this hypothesis, we proxy the wholesale market rate by the LIBOR having the same maturity as

[14] A null hypothesis of uniformity appears valid for this shorter 25 basis point above and below the integer range. The samples of predicted deposit rates described earlier show that the percentages of rates 25 basis points above the integer versus all rates 25 basis points above and below the integer were 50.001, 49.981, 50.013, and 50.004 for MMDAs, CD3s, CD6s, and CD12s, respectively.

the retail deposit.[15] We also attempt to control for possible independent sources of deposit rate stickiness that have been identified in previous research. As mentioned earlier, Hannan and Berger (1991) find deposit (MMDA) rates are stickier in more concentrated banking markets. Although Corollary 1 predicts that greater concentration increases banks' propensity to set rates at integer values, there may be other channels through which concentration affects stickiness. Thus, in testing the propensity to change deposit rates, we include a measure of local deposit market concentration—the Herfindahl index of the local metropolitan statistical area.[16] We also control for the extent of disequilibrium between market and deposit rates by including a variable that measures the spread between wholesale market and retail deposit rates.

More specifically, a bank's propensity to change its deposit rate at date $t$ is represented as a latent (unobserved) variable, $\boldsymbol{y}_t$. If $\boldsymbol{y}_t$ is less than some critical value, that is, $\boldsymbol{y}_t < \boldsymbol{y}^*$, then the bank chooses to lower its deposit rate; if $\boldsymbol{y}^* \leq \boldsymbol{y}_t \leq \boldsymbol{y}^* + \boldsymbol{c}$, then the bank chooses not to change its deposit rate; and lastly, if $\boldsymbol{y}^* + \boldsymbol{c} < \boldsymbol{y}_t$, then the bank chooses to raise its deposit rate.[17] $\boldsymbol{y}_t$ is assumed to depend on the change in the market (wholesale) rate, the degree of concentration in the bank's local deposit market, the spread between the market and deposit rates, and the basis-point region (mantissa) of last period's percentage deposit rate. The following linear relationship is assumed:

$$y_t = \beta_0 + \beta_1 \Delta r_t + \sum_{j=2}^{20} \beta_j d_j \cdot \Delta r_t + \beta_{21} \mu_t \cdot \Delta r_t + \beta_{22}(r_{t-1} - r_{d,t-1}) + \epsilon_t, \tag{7}$$

where $\Delta \boldsymbol{r}_t \equiv (\boldsymbol{r}_t - \boldsymbol{r}_{t-1})$ is the change in the wholesale market rate from date $t - 1$ to date $t$, the $\boldsymbol{d}_j$ are a set of dummy variables that indicate the basis-point region of $\boldsymbol{r}_{d,t-1}$, $\mu_t$ is the Herfindahl measure of bank deposit market concentration at date $t$, $(\boldsymbol{r}_{t-1} - \boldsymbol{r}_{d,t-1})$ is the spread between the market rate and the deposit rate at date $t - 1$, and $\epsilon_t$ is an independent, normally distributed error term. The inclusion of the set of dummy variables, $\boldsymbol{d}_j$, $j = 2,\ldots,20$, indicates whether rate stickiness depends on the basis points of the previously quoted percentage deposit rate. Since histograms of MMDA and CD rates indicate spikes at every five basis points, the basis-point region is divided into 20 subintervals, with the first being percentage rates having a mantissa of 0 to 4 basis points, the second being 5 to 9 basis points, up to the twentieth region being 95 to 99 basis points. The dummy variables $\boldsymbol{d}_j$,

[15] We use the one-month LIBOR in testing MMDA rates and the corresponding 3-, 6-, and 12-month LIBOR in testing CD3, CD6, and CD12 rates. LIBOR is for the last trading day of each month.

[16] Each bank's Herfindahl index is revised on an annual basis. The methodology for constructing this index is described in Berger and Hannan (1989) and Hannan and Berger (1991).

[17] $c$ defines an interval for the latent variable over which the bank does not change deposit rates. Movements in the latent variable are then determined by observed variables, such as changes in market rates and whether the deposit rate is currently at an integer level.

$j = 2,\ldots,20$, take on the value of 1 if the previous percentage deposit rate had a mantissa in the $j^{\text{th}}$ region, and 0 otherwise. Hence, for a given change in the wholesale market rate, $\Delta\boldsymbol{r}_t$, the coefficient $\beta_j$ measures the flexibility (lack of stickiness) of rates having a mantissa in the $j^{\text{th}}$ region ***relative*** to rates having a mantissa in the first region (0 to 4 basis points). Thus, a positive value for $\beta_j, j = 2,\ldots,20$, indicates that the rates in the first region (basically, the whole-integer level) are relatively stickier than rates in the $j^{\text{th}}$ region.

Since $\boldsymbol{y}_t$ is unobservable, we must rely on inferences made from an observable proxy, in this case the variable $\Delta\boldsymbol{r}_{dt}$, which is defined to equal 1 if there is a positive change in the bank's quoted deposit rate, 0 if there is no change, and $-1$ if there is a negative change.[18] Because $\Delta\boldsymbol{r}_{dt}$ is distributed in an ordered fashion, an ordered probit is an appropriate estimation technique.

The estimation results are reported in Table III. For each deposit type, the parameter estimates of the coefficients multiplying the market rate, $\Delta\boldsymbol{r}_t$, and the market deposit-rate spread, $(\boldsymbol{r}_{t-1} - \boldsymbol{r}_{d,t-1})$, have the expected positive signs and are highly significant. There is some evidence that deposit market concentration has independent effects on rate stickiness, as the coefficients of the Herfindahl index times the market rate change, $\mu_t\Delta\boldsymbol{r}_t$, are all negative, though statistically significant only for MMDAs and CD6s. Of most interest to the hypothesis that rates should be relatively stickier at integers are the coefficients of the basis-point dummy variables times the market rate change, $\boldsymbol{d}_j\Delta\boldsymbol{r}_t, j = 2,\ldots,20$. With the sole exception of the CD3, the point estimates of the coefficients of these variables are all positive, and most are statistically significant. When lack of significance does occur, it is often at the quarter, half, or three-quarter digit—that is, the coefficients on variables $\boldsymbol{d}_6\Delta\boldsymbol{r}_t$, $\boldsymbol{d}_{11}\Delta\boldsymbol{r}_t$, and $\boldsymbol{d}_{16}\Delta\boldsymbol{r}_t$. Taken together, these results support the model's prediction that deposit rates are stickiest when set at integer percentage rates, but that secondary stickiness also exists when rates are set at quarter-integer levels.

### *D. Market Rates, Concentration, and the Propensity for Integer and Quarter-Integer Deposit Rates*

Corollary 1, which is illustrated in Figure 2 (Panels A and B), predicts that a bank's propensity to quote integer-valued deposit rates should increase as market rates rise and as deposit market concentration increases. To test this hypothesis, we represent a bank's propensity to quote an integer deposit rate as another latent variable, $\boldsymbol{w}_t$. If $\boldsymbol{w}_t$ is less than some critical value, that is, $\boldsymbol{w}_t < \boldsymbol{w}^*$, then the bank chooses not to quote an integer percentage interest rate. If instead $\boldsymbol{w}_t \geq \boldsymbol{w}^*$, then the bank chooses to quote an integer rate. $\boldsymbol{w}_t$ is assumed to take the form

$$w_t = \beta_0 + \beta_1 r_t + \beta_2 \sigma_{r,t} + \beta_3 \mu_t + \epsilon_t, \tag{8}$$

[18] No change is defined to include interest rate movements where the percentage rate's mantissa remained within the same one-twentieth of a percentage point subinterval. These movements are extremely rare, and using the literal definition of no change does not affect our results.

## Table III
## Estimates of the Propensity to Change Deposit Rates

$$y_t = \beta_0 + \beta_1 \Delta r_t + \sum_{j=2}^{20} \beta_j d_j \cdot \Delta r_t + \beta_{21} \mu_t \cdot \Delta r_t + \beta_{22}(r_{t-1} - r_{d,t-1}) + \epsilon_t$$

The parameter estimates in the table are for an ordered probit model of retail deposit rate changes. The retail deposit rate data is from the Federal Reserve System's *Survey of Selected Deposits and Other Accounts* over the period November 1983 to May 1994. MMDA, CD3, CD6, and CD12 denote the money market deposit account rate, and 3-, 6-, and 12-month certificate of deposit rates, respectively. The definitions of the explanatory variables are as follows. $r_t$ is the equivalent maturity LIBOR at date $t$, with $\Delta r_t \equiv (r_t - r_{t-1})$. $d_i$, $i = 2, \ldots, 20$, are a set of dummy variables that indicate one of the 20 basis-point intervals of the mantissa of the date $t-1$ retail deposit rate, $r_{d,t-1}$. $\mu_t$ is the Herfindahl measure of bank deposit market concentration at date $t$. Numbers in parentheses are the standard errors of the parameter estimates.

| Coefficient of | MMDA | CD3 | CD6 | CD12 |
|---|---|---|---|---|
| $\Delta r_t$ | 103.85* | 120.46* | 130.63* | 101.53* |
| | (3.89) | (3.98) | (3.49) | (3.08) |
| $d_2 \Delta r_t$ : 5–9 bp | 24.41* | 46.19* | 43.12* | 40.59* |
| | (8.38) | (9.43) | (8.21) | (7.93) |
| $d_3 \Delta r_t$ : 10–14 bp | 3.98 | 20.76* | 21.61* | 40.04* |
| | (6.93) | (6.77) | (6.06) | (5.53) |
| $d_4 \Delta r_t$ : 15–19 bp | 27.26* | 41.15* | 42.05* | 52.15* |
| | (7.70) | (8.12) | (7.29) | (6.61) |
| $d_5 \Delta r_t$ : 20–24 bp | 18.95* | 38.94* | 27.31* | 54.66* |
| | (8.40) | (7.47) | (7.17) | (6.66) |
| $d_6 \Delta r_t$ : 25–29 bp | 1.66 | 0.55 | 8.90 | 21.00* |
| | (5.12) | (5.34) | (4.84) | (4.39) |
| $d_7 \Delta r_t$ : 30–34 bp | 22.06* | 20.71* | 22.31* | 47.97* |
| | (7.73) | (7.90) | (6.94) | (6.48) |
| $d_8 \Delta r_t$ : 35–39 bp | 24.29* | 24.43* | 11.12 | 45.56* |
| | (6.89) | (6.98) | (6.02) | (6.06) |
| $d_9 \Delta r_t$ : 40–44 bp | 23.12* | 46.52* | 29.46* | 46.72* |
| | (6.65) | (7.53) | (6.18) | (6.11) |
| $d_{10} \Delta r_t$ : 45–49 bp | 8.72 | 43.35* | 45.47* | 19.42* |
| | (7.98) | (9.82) | (8.64) | (6.96) |
| $d_{11} \Delta r_t$ : 50–54 bp | 2.20 | −2.58 | 13.73* | 17.93* |
| | (4.97) | (5.02) | (4.68) | (4.14) |
| $d_{12} \Delta r_t$ : 55–59 bp | 5.19 | 12.11 | 26.85* | 46.96* |
| | (8.58) | (8.30) | (7.63) | (7.29) |
| $d_{13} \Delta r_t$ : 60–64 bp | 41.14* | 22.55* | 17.96* | 26.77* |
| | (6.53) | (6.65) | (5.50) | (5.30) |
| $d_{14} \Delta r_t$ : 65–69 bp | 37.03* | 39.14* | 12.93 | 23.36* |
| | (7.80) | (8.51) | (7.13) | (6.45) |
| $d_{15} \Delta r_t$ : 70–74 bp | 73.77* | 15.82 | 33.02* | 37.81* |
| | (7.91) | (7.77) | (7.11) | (5.92) |
| $d_{16} \Delta r_t$ : 75–79 bp | 32.54* | −15.10* | 6.14 | 14.97* |
| | (5.44) | (5.08) | (4.73) | (4.24) |
| $d_{17} \Delta r_t$ : 80–84 bp | 26.60* | −5.73 | 38.99* | 51.44* |
| | (7.77) | (7.18) | (6.81) | (6.35) |
| $d_{18} \Delta r_t$ : 85–89 bp | 63.19* | 46.34* | 14.12* | 40.74* |
| | (7.91) | (7.84) | (6.04) | (5.90) |
| $d_{19} \Delta r_t$ : 90–94 bp | 51.96* | 43.11* | 28.13* | 33.14* |
| | (8.36) | (7.97) | (7.10) | (6.27) |
| $d_{20} \Delta r_t$ : 95–99 bp | 4.40 | 34.06* | 16.44 | 43.17* |
| | (10.62) | (9.77) | (9.13) | (8.11) |
| $\mu_t \Delta r_t$ : Herfindahl | −63.13* | −2.93 | −27.58* | −16.77 |
| | (10.21) | (10.44) | (9.37) | (8.71) |
| $r_{t-1} - r_{d,t-1}$ | 30.25* | 32.02* | 51.88* | 34.69* |
| | (0.63) | (0.65) | (0.76) | (0.52) |
| Total observations | 42,187 | 48,971 | 50,317 | 49,884 |

* Statistically significant at the 5 percent level.

**Table IV**

**Estimates of the Propensity to Set Integer Deposit Rates**

$$w_t = \beta_0 + \beta_1 r_t + \beta_2 \sigma_{r,t} + \beta_3 \mu_t + \epsilon_t$$

The parameter estimates in the table are for a probit model of the propensity to set retail deposit interest rates at integer levels. The retail deposit rate data is from the Federal Reserve System's *Survey of Selected Deposits and Other Accounts* over the period November 1983 to May 1994. MMDA, CD3, CD6, and CD12 denote the money market deposit account rate, and 3-, 6-, and 12-month certificate of deposit rates, respectively. The definitions of the explanatory variables are as follows. $r_t$ is the equivalent maturity LIBOR at date $t$, $\sigma_{r,t}$ is the annualized standard deviation of daily LIBOR during the month prior to date $t$, and $\mu_t$ is the Herfindahl measure of bank deposit market concentration at date $t$. Numbers in parentheses are the standard errors of the parameter estimates.

| Coefficient of | MMDA | CD3 | CD6 | CD12 |
|---|---|---|---|---|
| $r_t$ | 0.0485* | 0.0137* | 0.0130* | 0.0383* |
| | (0.0044) | (0.0038) | (0.0039) | (0.0034) |
| $\sigma_{r,t}$ | −0.1206 | 0.2525* | 0.5999* | 0.0378* |
| | (0.0651) | (0.0792) | (0.0797) | (0.0144) |
| $\mu_t$ : Herfindahl | 0.0569 | 0.1571* | −0.0410 | 0.3867* |
| | (0.0601) | (0.0584) | (0.0615) | (0.0552) |
| Total observations | 42,187 | 48,971 | 50,317 | 49,883 |
| % Obs. at integers | 15.81 | 13.15 | 11.56 | 14.11 |

* Statistically significant at the 5 percent level.

where $r_t$ is the market rate at date $t$, $\sigma_{r,t}$ is the standard deviation of the market rate, and $\mu_t$ is a measure of market concentration. Corollary 1 predicts a positive value for $\beta_1$, the coefficient of the market rate, which we again proxy by LIBOR.[19] Because the volatility of market rates, $\sigma_{r,t}$, tends to be positively correlated with the level of market rates, and greater volatility could have an independent influence on the tendency to quote integer rates, we also include a proxy for interest rate volatility—the annualized standard deviation of daily LIBOR during the previous month. Corollary 1 also predicts a positive value for $\beta_3$, the coefficient on the Herfindahl index of the individual bank's local deposit market.

The results of a probit estimation of equation (8) are given in Table IV. With the possible exception of the CD3, there is clear evidence that the propensity to set rates at an integer increases with the level of market rates. Moreover, greater market rate volatility appears to increase the likelihood that CDs are set at whole rates. Finally, there is weak evidence that integer rates are more common in more concentrated markets. The evidence is strong in the case of the CD12 and close to statistical significance for the CD3. The point estimate on the MMDA's concentration measure is of the correct sign, but it is not statistically significant.

[19] As before, we use LIBOR with a maturity equal to that of the corresponding retail deposit.

**Table V**

## Estimates of the Propensity to Set Quarter-Integer Deposit Rates

$$w_t = \beta_0 + \beta_1 r_t + \beta_2 \sigma_{r,t} + \beta_3 \mu_t + \epsilon_t$$

The parameter estimates in the table are for a probit model of the propensity to set retail deposit interest rates at quarter-integer levels. The retail deposit rate data is from the Federal Reserve System's *Survey of Selected Deposits and Other Accounts* over the period November 1983 to May 1994. MMDA, CD3, CD6, and CD12 denote the money market deposit account rate, and 3-, 6-, and 12-month certificate of deposit rates, respectively. The definitions of the explanatory variables are as follows: $r_t$ is the equivalent maturity LIBOR at date $t$, $\sigma_{r,t}$ is the annualized standard deviation of daily LIBOR during the month prior to date $t$, and $\mu_t$ is the Herfindahl measure of bank deposit market concentration at date $t$. Numbers in parentheses are the standard errors of the parameter estimates.

| Coefficient of | MMDA | CD3 | CD6 | CD12 |
|---|---|---|---|---|
| $r_t$ | 0.0726* | 0.0496* | 0.0527* | 0.0695* |
| | (0.0036) | (0.0030) | (0.0029) | (0.0028) |
| $\sigma_{r,t}$ | 0.1357* | 0.5541* | 0.4769* | 0.0135 |
| | (0.0537) | (0.0638) | (0.0640) | (0.0129) |
| $\mu_t$ : Herfindahl | 0.1875* | 0.2130* | 0.0877 | 0.2811* |
| | (0.0494) | (0.0471) | (0.0467) | (0.0466) |
| Total observations | 42,187 | 48,971 | 50,317 | 49,883 |
| % Obs. at quarters | 48.49 | 45.60 | 40.66 | 41.88 |

* Statistically significant at the 5 percent level.

Based on Figure 3's evidence of a tendency to quote quarter-integer deposit rates, a natural question is whether this propensity is also related to the level of market rates and concentration. If the theoretical model of Section I is modified to consider naive investors whose recall is at quarter-integers, then a version of Corollary 1 would imply that quarter-integer quotes should be more likely at higher levels of market rates and concentration. Thus, we reestimate equation (8), except that the dependent variable is the propensity to be at any quarter-integer (a mantissa of 0.00, 0.25, 0.50, or 0.75).

The results are given in Table V, and they provide even stronger support for the general implications of our theory. The propensity to quote quarter-integer deposit rates increases with the level of market rates, the volatility of market rates, and the level of concentration. These effects are statistically significant at the 5 percent level for nearly all deposit types, the sole exceptions being the insignificance of volatility on CD12s and the 10 percent statistical significance of concentration on the CD6.

### *E. The Prevalence of Limited Recall in MMDA Markets*

The extent of integer-rate clustering and noninteger rate asymmetry in our sample of deposit rates can provide information on the proportion of depositors having limited recall. Given a specification for our basic model's deposit demand function, estimates of the proportion of naive depositors, $\kappa$, that are consistent with the deposit rate data's integer clustering and noninteger asymmetry can be computed. This section provides such estimates for MMDAs, where clustering and asymmetry are most prevalent. Since computing these estimates requires a number of simplifying assumptions, they should be treated with caution and viewed as merely suggestive of the degree of limited recall in MMDA markets.

If depositor demand is specified as the simple linear form $D = a_0 + a_1 r + a_2 r_d$, then the bank's profit maximizing deposit rate (in the absence of naive depositors) is a linear function of the market interest rate: $r_d^s = \frac{1}{2}[(1 - a_1/a_2)r - c - a_0/a_2]$. To obtain rough estimates of the parameters $a_0/a_2$ and $a_1/a_2$, we regress each MMDA rate in our sample on its contemporaneous one-month LIBOR value. The intercept of this regression is taken as an estimate of $-\frac{1}{2}(c + a_0/a_2)$ while the coefficient on LIBOR proxies for $\frac{1}{2}(1 - a_1/a_2)$.[20] Assuming a noninterest expense per deposit parameter of $c = 0.004517$ (45 basis points) results in highly significant estimates of $a_0/a_2 = -0.01675$ and $a_1/a_2 = -0.4003$.[21]

Having estimates for $a_0/a_2$, $a_1/a_2$, and $c$, and given a value for the proportion of naive depositors, $\kappa$, a bank's optimal deposit rates, $r_d^*$, could now be calculated for any market interest rate, $r$, using the rule in Theorem 1. Therefore, we fix $\kappa$ and calculate a time series of optimal deposit rates by assuming that the market interest rate equals the actual one-month LIBOR for each day in our sample period, November 30, 1983 to May 31, 1994.[22] This results in a set of 2,964 deposit rates for each assumed value of $\kappa$ which we let vary from 0 to 20 percent.

To see how the extent of integer-rate clustering changes with the proportion of naive depositors, we then calculate from each set of deposit rates (each set corresponding to a different $\kappa$) the percentage of rates set at inte-

[20] Since this linear relation holds only for $\kappa = 0$, the estimates are biased when $\kappa > 0$. In principle, one could estimate these parameters for a given level of $\kappa$ using data on $r$ and $r_d$ for each individual bank. This would require a numerical technique based on the nonlinear rule given in Theorem 1. For this $\kappa$ and its corresponding set of parameter estimates, one could generate a set of hypothetical deposit rates using the actual market rates occurring during the sample period. From these deposit rates, the percentage of integer rates and percentage of noninteger rates in the above-integer range could be computed. This procedure could be repeated by iterating over values of $\kappa$ (and corresponding estimates for $a_0/a_2$ and $a_1/a_2$) until the value of $\kappa$ most consistent with a bank's degree of integer rate clustering and/or noninteger rate asymmetry is found. Due to the computational complexity of this approach, our simpler method is chosen. However, since Theorem 1 says that $r_d^*$ should be "close" to $r_d^s$, the bias in our estimates is limited. As a check of robustness, we consider a range of alternative parameters estimates and find only small changes in our quantitative results.

[21] The $t$-statistics equal 31.6 and 296.6, respectively, and the $R^2$ is 0.68. The value for $c$ is estimated by Hutchison and Pennacchi (1996) from the Federal Reserve's *Functional Cost Analysis* data.

[22] Simulating a daily time-series of hypothetical MMDA rates gives us 2,964 observations for each assumed value of $\kappa$ on which to base our calculations, as opposed to only 127 observations if a monthly time-series is simulated. However, results using a monthly simulation are substantially similar.

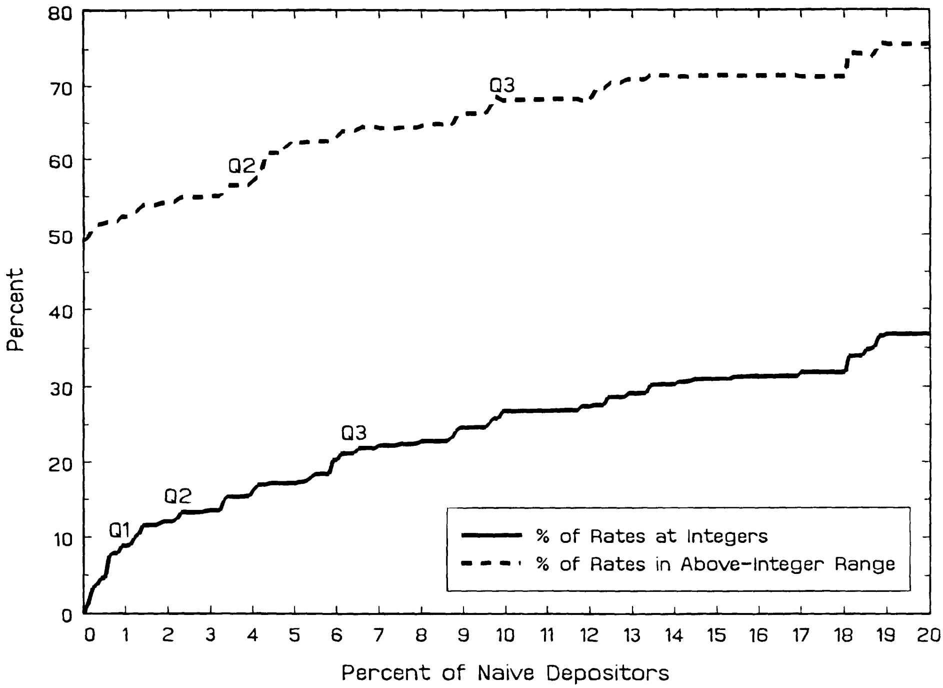


**Figure 4. Percentages of deposit rates set at integers and just-above integers.** Assuming a linear deposit demand function with parameters estimated from the sample of MMDA rates, the figure shows the percentage of deposit rates that should be set at integers and the percentage of deposit rates (excluding whole- and half-integers) that should be in the 1 to 49 basis point (above-integer) range. The percentages are graphed as a function of the percent of naive depositors in the population. Actual percentages of MMDA rates set at integers and in the above-integer range are also calculated for each individual bank in our sample, and Q1, Q2, and Q3 indicate the first-quartile, median, and third-quartile percentages for this cross section of individual banks.

gers. We also calculate the percentage of rates in the above-integer 1 to 49 basis point range versus all noninteger and non-half-integer rates (rates from 1 to 49 basis points and 51 to 99 basis points) for each of these sets of deposit rates. These results, for each value of $\kappa$, are plotted in Figure 4.

Recalling from Figure 3 that 15.6 percent of the rates in the MMDA sample are set at integers, we can see from Figure 4 that the implied value of $\kappa$ based on this total sample's integer clustering is approximately 4.0 percent. Alternatively, based on Table II's reporting that 55.83 percent of the total MMDA sample has noninteger rates in the above-integer 1 to 49 basis point range, the implied value of $\kappa$ is approximately 3.4 percent. It is noteworthy that these two estimates for $\kappa$ are relatively close to each other, even though they are each based on two quite different characteristics of the data. This would appear to provide more informal support for the limited recall hypothesis.

These two estimates for the proportion of naive depositors are based on clustering and asymmetry characteristics averaged across all banks. Hence, they cannot account for differences in the proportion of naive depositors in different banking markets. To allow for bank-specific differences, we compute the actual percentages of MMDA rates at integers and the percentages of noninteger rates in the above-integer range on a bank-by-bank basis. We do this for each of the 459 banks in our sample that has at least 50 MMDA rate observations. The resulting first quartile (Q1), median (Q2), and third quartile (Q3) of these banks ranked by their degree of integer clustering or noninteger asymmetry are also plotted in Figure 4.[23]

The individual bank estimates of $\kappa$ based on integer clustering display somewhat less variation across banks than do the estimates based on noninteger asymmetry. The median and third-quartile clustering-based estimates of $\kappa$ are 1.9 percent and 6.0 percent, respectively, and the median and third-quartile asymmetry-based estimates of $\kappa$ are 3.4 percent and 9.6 percent, respectively. Yet, it is apparent that using either integer clustering or noninteger asymmetry as a gauge, reasonably small levels of limited recall can generate our sample's clustering and asymmetry. Even for banks at the third quartile, the estimated proportion of naive depositors is always less than 10 percent. Thus, it appears that relatively modest levels of limited recall can significantly affect banks' pricing of retail deposits.

## III. Conclusions and the General Implications of Limited Recall

This paper examines a bank's optimal strategy for setting deposit interest rates when some of its customers have limited recall. Taking seriously the experimental evidence that individuals recall odd-ending numbers less accurately than even-ending numbers and that odd-ending numbers are more likely to be underestimated when recalled, we model deposit demand by limited recall customers as being a function of the floor of the percentage deposit interest rate. Our analysis indicates that a bank optimally sets its percentage deposit rate either at a whole integer or at an interior point that satisfies a specific first-order condition.

The model predicts that the likelihood of deposit rates being quoted as an integer increases with the proportion of a bank's depositors having limited recall, with increases in the wholesale market interest rate, and with increases in the level of deposit market concentration. It also predicts that when banks set noninteger rates, they are more likely to be just above, rather than just below, integer values. Further, for a given wholesale market rate shock, the quoted deposit rate tends to be stickier when it is currently at an integer than when it is not. Our tests using monthly MMDA and CD interest

[23] The percent of noninteger rates in the above-integer range for the first quartile bank is 45.6 percent.

rates for more than 600 individual banks during a $10\frac{1}{2}-$ year period provide evidence supporting the model's implications. The empirical results also suggest that only small degrees of limited recall are needed to generate substantial effects on banks' deposit pricing behavior.

This paper's theoretical framework and empirical techniques can be used to investigate the presence of limited recall in other markets for retail products and services. Research examining evidence for limited recall in markets for consumer loans, such as automobile loans, personal unsecured loans, and home-equity lines of credit, is currently underway. Preliminary results indicate that limited recall appears to be even more pervasive in consumer loan markets than in consumer deposit markets. This suggests that limited recall and its effects on the pricing of retail financial services is a widespread phenomenon.

The finding that modest levels of limited recall can produce significant price clustering and stickiness has potentially important consequences for both micro- and macroeconomics. At the micro level, limited recall affects consumer demand, thereby influencing the efficiency of market allocations. However, the efficiency enhancing remedies in markets with limited recall are generally different from those in markets where price clustering results from collusive agreements. When inefficiency stems from collusion, antitrust remedies are necessary, perhaps including penalties against the colluding parties or changes in exchange rules that make tacit collusion more difficult. In contrast, successful interventions in markets characterized by limited recall need to be less coercive: actions enhancing the information available to transactors often suffices. Mechanisms that facilitate comparison shopping by consumers, in effect making it easier for them to remember and compare the details of competing offers, improve allocational efficiency.[24]

At the level of macroeconomics, the consequences of limited recall may differ from those of other potential causes of price stickiness. "Menu costs," that is, costs directly associated with changing prices, have been used to account for price stickiness and are the basis of many neo-Keynesian macroeconomic models.[25] One result of this literature, which appears to hold for both the menu cost and limited recall approaches, is that small costs of adjusting prices can result in significant price stickiness that has a large real impact on the economy. However, the two approaches may diverge in terms of the dynamics of price changes: Limited recall, unlike menu costs,

[24] These mechanisms may arise endogenously in response to consumer demand. For example, many newspapers list the current retail loan and deposit interest rates offered by their local banks. On a national level, *Bank Rate Monitor, Inc.* provides this information on the Internet. In general, an increase in the number of firms that advertise prices on media such as the Internet should facilitate comparison shopping.

[25] For example, see Mankiw and Romer (1991). An alternative explanation of price stickiness, with some connection to limited recall, is rounding error in data collection. For an examination of this phenomenon with respect to earnings data, see Schweitzer and Severance-Lossin (1997).

predicts that the degree of price stickiness is contingent on whether current prices are "even" or "odd" fractions. A useful extension would be to compare the welfare consequences of these two sources of price stickiness.

## Appendix. Derivation of the Bank Deposit Demand Equation

This appendix provides a rationale for the form of the deposit demand equations of sophisticated and naive depositors, equations (1) and (2) in the text. It shows how linear versions of these demand equations can be derived by aggregating the deposit demands of individuals who differ in terms of their alternative market-linked investments.

Assume that individual depositors' demands depend on the bank's deposit rate, $r_d$, and their individual alternative investment rate, which for depositor $i$ is given by $r_i$. For a given depositor, this alternative investment rate may be the yield on a particular money market mutual fund, whereas for another depositor, it may be the yield on a different money fund, a Treasury bill yield, the yield on a corporate bond mutual fund, the yield on a tax-free municipal bond fund, a GNMA fund yield, or even the yield on a U.S. savings bond. The idea is that different depositors may view different investments as their primary alternative to bank MMDAs and CDs.

We assume that $r_i = r - \epsilon_i$, where $\epsilon_i$ is a constant spread between the bank's wholesale investment rate, $r$, and depositor $i$'s alternative investment rate. To simplify the aggregation of individual demand functions, let individual demands be linear, so that the deposit demand of sophisticated depositor $i$ is given by

$$\begin{aligned} D_i &= a + a_1 r_i + a_2 r_d = a + a_1(r - \epsilon_i) + a_2 r_d \\ &= a - a_1\epsilon_i + a_1 r + a_2 r_d. \end{aligned} \tag{A1}$$

The bank is assumed to face a continuum of sophisticated depositors with unit mass whose individual spreads, $\epsilon_i$, are uniformly distributed over the interval (0,1); that is, the individual depositors' alternative investment rates range from zero to 100 basis points less than the bank wholesale funding rate, $r$. This implies that the bank's aggregate demand function for sophisticated depositors is

$$\begin{aligned} D &= a - \tfrac{1}{2}a_1 + a_1 r + a_2 r_d \\ &= a_s + a_1 r + a_2 r_d, \end{aligned} \tag{A2}$$

where $a_s \equiv a - \frac{1}{2}a_1$.

In a similar manner, the deposit demand of individual naive (limited recall) depositor $i$ is given by

$$D_i = a + a_1[r_i]_- + a_2[r_d]_- = a + a_1[r - \epsilon_i]_- + a_2[r_d]_-. \tag{A3}$$

Now if $\epsilon_i \leq r - [r]_-$, then $[r - \epsilon_i]_- = [r]_-$. Assuming there is a continuum of naive depositors with unit mass, this case occurs for a proportion $(r - [r]_-)$ of the naive depositors. If, instead, $\epsilon_i > r - [r]_-$, then $[r - \epsilon_i]_- = [r - 1]_-$. This case occurs for a proportion $1 - (r - [r]_-)$ of the naive depositors. Thus, aggregating the individual naive depositors' demands, the bank's aggregate demand for naive depositors, $D^n$, is

$$D^n = a + a_1\{(r - [r]_-)[r]_- + (1 - r + [r]_-)[r - 1]_-\} + a_2[r_d]_-. \tag{A4}$$

Simplifying the expression in brackets by noting that $[r]_- - [r - 1]_- = 1$, we obtain

$$\begin{aligned} D^n &= a + a_1\{r - 1\} + a_2[r_d]_- \\ &= a_n + a_1 r + a_2[r_d]_-, \end{aligned} \tag{A5}$$

where $a_n \equiv a - a_1$. Thus, the aggregate demand of a bank's naive depositors depends on the floor of the bank's deposit rate, but on the actual wholesale market interest rate.

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