ARE BANKS RISK-AVERSE?

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INTRODUCTION

Banks typically operate by extending long-term assets (loans) that are funded primarily by short-term liabilities (deposits), thereby exposing themselves to interest-rate risk. In a period of rising market interest rates, for example, such maturity mismatching implies a decline in income and/or net worth because liabilities reprice faster than assets (or interest-rate risk). A recent study [Sierra and Yeager, 2004] shows, however, that banks in general are only moderately liability sensitive, thereby suggesting that the degree of mismatching may be limited. This finding is consistent with the fact that interest-rate risk control measures are in place at banks in order to limit adverse impacts of interest-rate risk [Houpt and Embersit, 1991]. Also, it is consistent with the risk-averse behavior of banks [Niehans and Hewson, 1976; Niehans, 1978].

The primary objective of this paper is to find out empirically banks' risk preferences (whether or not, and to what extent, banks are risk-averse) that underlie duration[1]/maturity matching or mismatching. This study serves three purposes. First, there is only scant empirical evidence for banks' risk preferences (for example, Ratti [1980] and Angelini [2000]).[2] Second, the Federal Reserve System developed a duration-based economic value model that estimates the sensitivity of market-value equity to changes in interest rates for each U.S. commercial bank [Houpt and Embersit, 1991; Wright and Houpt, 1996; Sierra and Yeager, 2004]. The model, a surveillance tool for bank examiners/supervisors, was operationalized in the first quarter of 1998 [Sierra and Yeager, 2004]. At a more fundamental level, however, it is likely to be informative for bank examiners/supervisors to know banks' risk preferences that underlie these sensitivity estimates. Lastly, and most importantly, the paper is closely related to the issue of deposit rate rigidity examined by Neumark and Sharpe [1992] who provide empirical evidence that both the rate on a time deposit (the six-month certificate of deposit or CD) and the rate on a non-time deposit (money market deposit account or MMDA) move sluggishly relative to open market yields. They find that banks in more concentrated markets are slower to adjust these deposit rates upward, but are faster to adjust them downward. Hence, "banks with market power skim off surplus on movements in both directions" [Neumark and Sharpe, 1992, 657]. In addition, the MMDA rate is found to be more sluggish than the CD rate due to their contractual differences.[3] It is this last finding of Neumark and Sharpe [1992] on which this paper throws new light beyond simply contractual differences.

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To see the relation between this paper and Neumark and Sharpe [1992], consider a typical bank with mismatched durations, $d_A - d_L > 0$[4] (a positive duration gap) where d_A = weighted-average duration (or maturity) of assets and d_L = weighted-average duration (or maturity) of liabilities. In an environment of rising market interest rates, the bank may lengthen the duration of liabilities (deposits) by increasing its relative holdings of longer-term deposits – if it is risk-averse. This strategy requires the bank to raise interest rates on longer-term deposits (for which six-month CDs are used in this paper) above those on short-term deposits (for which MMDAs are used in this paper), thereby increasing the interest rate spread between the two maturities (CDs over MMDAs) while narrowing the duration gap (i.e., duration matching). Given that market interest rates are known to be procyclical [Stock and Watson, 1999], an alternative interpretation of this strategy is that interest rates on longer-term deposits (CDs) are procyclically more flexible than interest rates on short-term deposits (MMDAs) – if the bank is risk-averse – hence providing a new insight beyond contractual differences noted by Neumark and Sharpe [1992]. (The case of falling market interest rates can be symmetrically explained. See Rose [2002]).

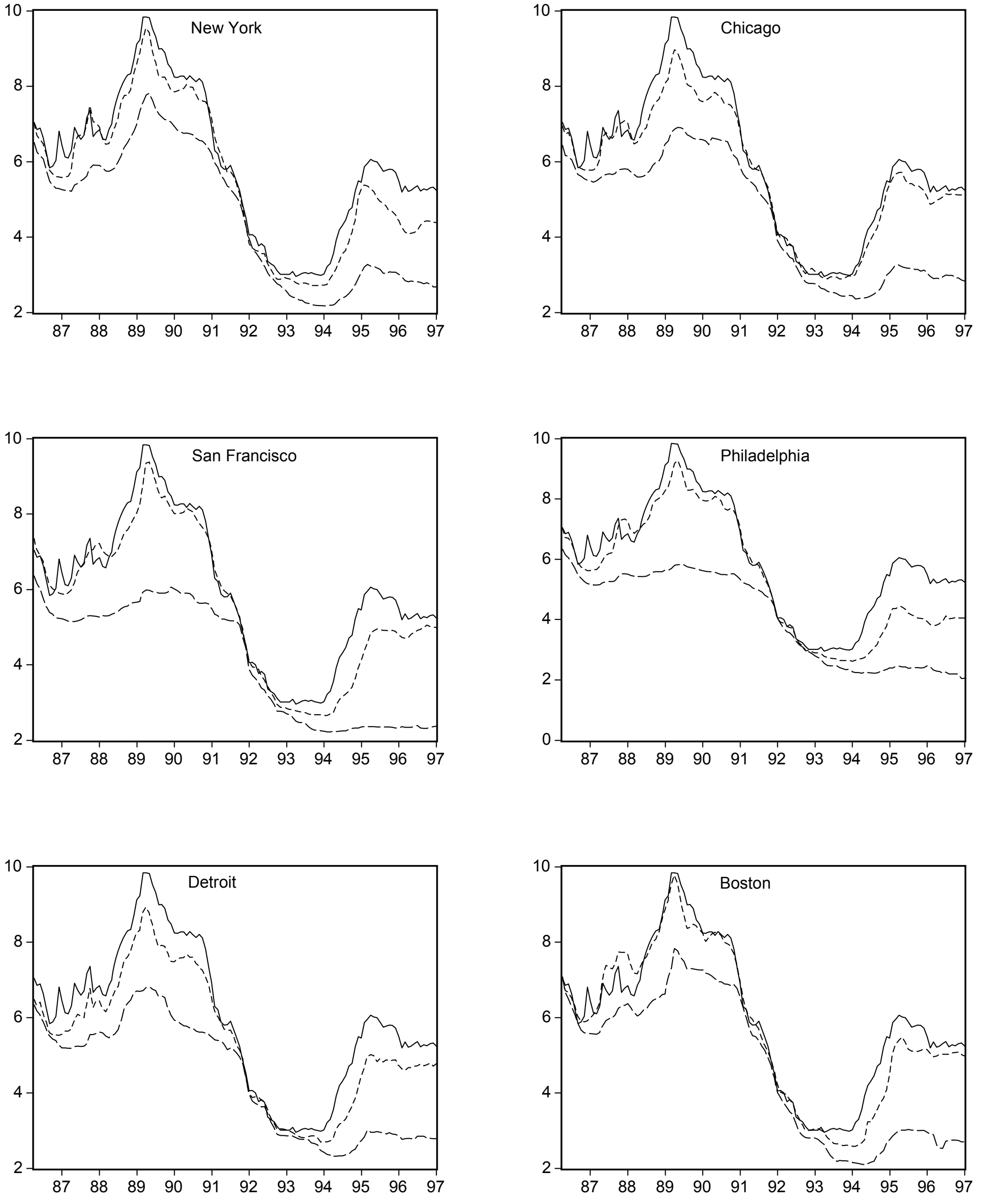
This paper extends Neumark and Sharpe [1992] by advancing two factors to explain why the MMDA rate is more sluggish than the CD rate while the paper's main question (whether or not banks are risk-averse) is also jointly answered. The first factor is duration matching and banks' risk aversion (as explained above). The second factor is the term structure of CD rates (or the yield spread between longer-term CDs and short-term CDs), the details of which are explained below.[5] The main conclusion in this paper based on regressions of selected individual banks is that the average of relative risk aversion (RRA) coefficient estimates falls between 0 and 1 (most likely around 0.2) and hence banks are risk-averse. However, the estimates are very close to zero, suggesting that banks may be nearly risk-neutral.

Figure 1 shows the data used in this paper. It extends the sample period (1983-87) of Neumark and Sharpe [1992], showing the federal funds rate, the rate on MMDAs and the rate on six-month consumer CDs during the 1986-97 period for six cities. (The data of interest rates and the choice of these six cities are explained in Appendix A.) It is clear that the sluggishness of deposit rates (more so in the case of the MMDA rate) relative to market interest rates (the federal funds rate in this paper; the six-month Treasury bill rate in Neumark and Sharpe [1992]) during the sample period of Neumark and Sharpe [1992] has not changed in later years.

The paper proceeds as follows. I develop an intertemporal bank model in the next section and derive two factors that explain the greater flexibility of the CD rate than the MMDA rate. Then, the paper focuses exclusively on the first factor (duration matching and risk aversion) in order to uncover a presumed positive relationship between the degree of risk aversion and the correspondingly desired degree of the CD-MMDA rate spread. Next, the empirical specification that includes both factors is derived, followed by a brief data description, and the estimation results. The final section gives a summary.

FIGURE 1
The Federal Funds Rate, the MMDA Rate and the 6-Month Consumer CD Rate

——— Federal Funds Rate
- - - - - 6-Month Consumer CD Rate
– – – – MMDA Rate
Note: Numbers on the vertical axis are in percent.



WHY ARE CD RATES MORE FLEXIBLE THAN MMDA RATES? – TWO FACTORS

The bank model in this paper is an intertemporal version of the well-known Monti-Klein model [Klein, 1971; Monti, 1972] where a representative bank behaves monopolistically, setting both its loan and deposit rates. The bank's asset and liability position at the end of period t is as follows.

Assets:

$L_{2,t-1}$ = two-period loans, booked at t-1, interest paid at t, and repaid with interest at t+1
$L_{1,t}$ = one-period loans, booked at t, and repaid with interest at t+1
$L_{2,t}$ = two-period loans, booked at t, interest paid at t+1, and repaid with interest at t+2
FS_t = federal funds sold
B_t = government securities
R_t = rD_t (total required reserves) where r denotes the reserve requirement ratio (D_t is explained below).

Liabilities and equity capital:

D_t = non-interest-bearing transaction deposits, given exogenously
$D_{m,t}$ = interest-bearing transaction deposits, represented by MMDAs
$D_{c1,t}$ = one-period CDs, issued at t, and mature with interest at t+1
$D_{c2,t-1}$ = two-period CDs, issued at t-1, interest paid at t, and mature with interest at t+1
$D_{c2,t}$ = two-period CDs, issued at t, interest paid at t+1, and mature with interest at t+2
FP_t = federal funds purchased
K_t = equity capital, given exogenously.

The demand function for both one-period and two-period loans (hence omitting the subscripts 1 and 2) is $L_t(\iota_t;Y_t)$ where ι_t denotes the interest rate on loans; Y_t denotes the level of economic activity, given exogenously; $\partial L_t/\partial\iota_t < 0$ and $\partial L_t/\partial Y_t > 0$. For each of MMDAs and CDs, I assume a simple constant-elasticity deposit supply function of the following form (omitting the subscripts): $D = ai^e$ where D and i denote the supply of deposits and the interest rate, respectively; a is a constant ($a > 0$); and e denotes the constant elasticity ($e > 0$). To simplify, it is assumed that the bank holds government securities only to manage liquidity, justifying $B_t = B$ (constant).

The balance sheet constraint is expressed by: $FS_t - FP_t = (1-r)D_t + D_{m,t} + D_{c2,t-1} + D_{c1,t} + D_{c2,t} + K_t - L_{2,t-1} - L_{1,t} - L_{2,t} - B$ where $FS_t - FP_t > 0$ (< 0) indicates the bank's net excess reserves (net reserves shortages) that are lent (borrowed) in the federal funds market. The bank's profit during period t is expressed as

$$\pi_t = \iota_{2,t-2}L_{2,t-2} + \iota_{1,t-1}L_{1,t-1} + \iota_{2,t-1}L_{2,t-1} + i_{f,t}(FS_t - FP_t) + i_{b,t}B$$
$$- i_{m,t}D_{m,t} - i_{c2,t-2}D_{c2,t-2} - i_{c1,t-1}D_{c1,t-1} - i_{c2,t-1}D_{c2,t-1} - C(TL_t, TD_t) - FC$$

where

$\iota_{n,t-j}$ = interest rate on n-period loans that are booked at t-j (n = 1, 2; j = 1, 2)
$i_{m,t}$ = interest rate on MMDAs
$i_{cn,t-j}$ = interest rate on n-period CDs that are issued at t-j (n = 1, 2; j = 1, 2)
$i_{f,t}$ = federal funds rate, given exogenously
$i_{b,t}$ = yield on government securities, given exogenously
$C(TL_t, TD_t)$ = noninterest cost function with $C_l = \partial C / \partial TL_t > 0$, $TL \equiv L_{2,t-1} + L_{1,t} + L_{2,t}$, $C_d = \partial C / \partial TD_t > 0$, and $TD_t \equiv D_t + D_{m,t} + D_{c1,t} + D_{c2,t-1} + D_{c2,t}$
FC = fixed cost.

The federal funds rate is the source of uncertainty for the bank in the model. The marginal costs (MC) of deposits and loans, C_d and C_l, are assumed to be constant.

Subject to the balance sheet constraint, the bank maximizes the expected value of the time-separable utility function $u(\pi_t)$, $E_t \sum_{s=t}^{\infty} \beta^{s-t} u(\pi_s)$, with respect to time-t loan and deposit rates where π_s denotes period-s profit and β denotes the subjective discount factor. The relevant first order conditions are (* denotes the optimal rate):

$$i_{m,t}^{*} = (1 + e_m^{-1})^{-1}(i_{f,t} - C_d) \tag{1}$$

$$i_{c1,t}^{*} = (1 + e_{c1}^{-1})^{-1}E_t(M_{t+1})^{-1}(i_{f,t} - C_d) \tag{2}$$

$$i_{c2,t}^{*} = (1 + e_{c2}^{-1})^{-1}E_t(M_{t+1})^{-1}(i_{f,t} - C_d)V_t \tag{3}$$

where

e_m, e_{c1}, e_{c2} = elasticity of deposit supply (MMDA, one-period CD, two-period CD, respectively)
C_d = constant MC (noninterest marginal cost)
M_{t+1} = intertemporal marginal rate of substitution (IMRS) of present (time t) for future (time t+1) profit, $M_{t+1} = \beta u'(\pi_{t+1}) / u'(\pi_t)$, and similarly $M_{t+2} = \beta u'(\pi_{t+2}) / u'(\pi_{t+1})$
V_t = $\{1 + [E_t[M_{t+1}(i_{f,t+1} - C_d)] / (i_{f,t} - C_d)]\} / \{1 + [E_t(M_{t+1}M_{t+2}) / E_t(M_{t+1})]\}$.

It is assumed that $i_{f,t} > C_d$.

The paper's main objective is to estimate the spread, $\log(i_{c2,t}^{*}) - \log(i_{m,t}^{*})$, which is related to two factors discussed in the introduction as follows (here assuming $e_m = e_{c1} = e_{c2}$ for simplicity):

$$\log(i_{c2,t}^{*}) - \log(i_{m,t}^{*}) = \underbrace{[\log(i_{c1,t}^{*}) - \log(i_{m,t}^{*})]}_{\text{First factor} = -\log E_t(M_{t+1})} + \underbrace{[\log(i_{c2,t}^{*}) - \log(i_{c1,t}^{*})]}_{\text{Second factor} = \log V_t}. \tag{4}$$

Both the first factor and the second factor account for time variations in the spread. The next section explains how the first factor is related to risk aversion and duration matching. The second factor is related to the economy-wide term structure of interest rates. To see this relationship clearly, assume $M_{t+j} = 1$ (j = 1, 2) which arises under, for example, $\beta = 1$ and risk-neutrality (i.e., a linear utility function). Then, using equations (2) and (3), $i_{c2,t}^{*}$ can be rewritten as

$$\begin{aligned} i_{c2,t}^{*} &= (1 + e_{c2}^{-1})^{-1}\{ [(i_{f,t} + E_t(i_{f,t+1})) / 2] - C_d\} \\ &= (1 + e_{c1}^{-1})(1 + e_{c2}^{-1})^{-1} [(i_{c1,t}^{*} + E_t(i_{c1,t+1}^{*})) / 2]. \end{aligned}$$

A change in expected future monetary policy, $E_t(i_{f,t+1})$,[6] that affects the economy-wide term structure of interest rates (the first line above) also affects the term structure of bank CD rates (the second line above). In general, however, expectations of future monetary policy and IMRSs are intertwined in the V_t term.

In order to avoid notational clutter, a subscript "c" is used throughout below instead of "c1" and "c2." The next section uses "c" for "c1" and the rest of the paper uses "c" for "c2."

RISK AVERSION—THE FIRST FACTOR

As noted above, this subsection limits the model to one-period CDs and one-period loans: assume "c" = "c1" in this section. Therefore the notation used here is as follows: all i_c , e_c and D_c refer to one-period CDs, and all ι and L refer to one-period loans.

Following previous papers [Mehra and Prescott, 1985; Hansen and Jagannathan, 1991; Campbell, 1999; Feldstein and Ranguelova, 2001; and others], I assume that the utility function is isoelastic:

$$u(\pi_t) = (\pi_t^{1-\gamma} - 1)/(1-\gamma)$$

where γ = coefficient of relative risk aversion (RRA).

If Jensen's inequality[7] is ignored for expositional simplicity, i.e., assuming $\log E_t(M_{t+1}) = E_t \log(M_{t+1}) = E_t \log(\beta u'(\pi_{t+1}) / u'(\pi_t))$, then $\log E_t(M_{t+1}) = \log\beta - \gamma E_t \log(\pi_{t+1} / \pi_t)$ and the first term on the right-hand side of equation (4) is expressed as

$$(5) \qquad \begin{aligned} \log(i_{c,t}^{*}) - \log(i_{m,t}^{*}) &= - \alpha_c + \alpha_m - \log E_t(M_{t+1}) \\ &= - \alpha_c + \alpha_m - \log\beta + \gamma E_t \log(\pi_{t+1} / \pi_t), \end{aligned}$$

where $\alpha_c = \log(1 + e_c^{-1})$ = constant
$\alpha_m = \log(1 + e_m^{-1})$ = constant.
$\pi_t > 0$ and $\pi_{t+1} > 0$ are assumed. (In practice, $\pi_t < 0$ occurs on rare occasions. See footnote 20.)

If MMDAs are competed for locally while CDs are competed for on a broader geographic basis [Berger and Hannan, 1989; Hannan and Liang, 1993], then the elasticity of deposit supply of CDs is likely to be greater than the elasticity of deposit supply of MMDAs [Hannan and Liang, 1993], i.e., $e_c > e_m$, leading to $-\alpha_c + \alpha_m > 0$ and therefore $\log(i_{c,t}^*) - \log(i_{m,t}^*) > 0$. This positive and constant spread, however, is not capable of explaining observed time variations in the spread shown in Figure 1. Notice that the spread varies substantially over time and procyclically, suggesting that a satisfactory explanation for these procyclical variations in the spread comes from the last term in equation (5) which differentiates time deposits (CDs) from non-time deposits (MMDAs).

In order to illustrate the main point (that the spread, or the first factor, is related to banks' risk aversion) unambiguously, assume the following: $\pi_t = \pi_{t+1}$ = constant > 0 (initially), $\beta = 1$, $e_c = e_m$, the identical deposit supply function for $D_{m,t}$ and $D_{c,t}$, $FS_t = FP_t$ and $FS_{t+1} = FP_{t+1}$. Furthermore, Y_{t+1} and $i_{f,t+1}$ are assumed constant in order to isolate effects of the procyclical rise in Y_t and $i_{f,t}$. Now, suppose a procyclical deterministic rise in Y_t and $i_{f,t}$[8] ($\Delta Y_t > 0$ and $\Delta i_{f,t} > 0$), thereby causing an increase in loan demand, $\Delta L_t > 0$. To fund this increased loan demand, the bank increases the MMDA rate in order to obtain $\Delta D_{m,t} > 0$ and/or increase the CD rate in order to obtain $\Delta D_{c,t} > 0$, assuming that $\Delta L_t = \Delta D_{c,t} + \Delta D_{m,t} > 0$. Then, it can be shown that the first-order Taylor approximation of equation (5) gives (omitting * for notational simplicity)[9]

$$(6)\quad \gamma = (\pi_t / i_{c,t})(\Delta i_{c,t} - \Delta i_{m,t}) \,/\, [\, (\iota_t + C_l + C_d)\Delta L_t + L_t \Delta\iota_t - D_{m,t}(1 + e_m)(\Delta i_{c,t} - \Delta i_{m,t}) \,],$$

where $\Delta L_t = (\partial L_t / \partial Y_t)\,\Delta Y_t + (\partial L_t / \partial \iota_t)\Delta\iota_t = \Delta D_{c,t} + \Delta D_{m,t}$, $\Delta D_{c,t} = (dD_{c,t} / di_{c,t})\Delta i_{c,t}$, and $\Delta D_{m,t} = (dD_{m,t} / di_{m,t})\Delta i_{m,t}$.

Equation (6) shows that for a given procyclical increase in loan demand $\Delta L_t > 0$, γ and $\Delta i_{c,t} - \Delta i_{m,t}$ are positively related. If a bank is risk-neutral ($\gamma = 0$), then $\Delta i_{c,t} = \Delta i_{m,t}$. In this case, it is optimal for the bank to raise the CD rate and the MMDA rate by the same amount. For a risk-averse bank with $\gamma > 0$, however, it is optimal to raise more funds through new CDs (than through new MMDAs) by raising the CD rate higher than the MMDA rate (i.e., $\Delta i_{c,t} - \Delta i_{m,t} > 0$). Clearly, the greater the degree of risk aversion, the greater the difference $\Delta i_{c,t} - \Delta i_{m,t}$. It implies that the duration gap, defined by $d_{loan} - [(\Delta D_{m,t} / \Delta L_t)\, d_m + (\Delta D_{c,t} / \Delta L_t)\, d_c] = 1 - (\Delta D_{c,t} / \Delta L_t)$, narrows (i.e., duration matching) because $\Delta D_{c,t} / \Delta L_t$ is larger. (d_{loan}, d_m, and d_c are the durations of loans, MMDAs, and CDs, respectively. Since loans and time deposits in this section have simple one-period maturity, their durations and maturities are identical, that is, $d_{loan} = 1$ and $d_c = 1$. $d_m = 0$ because MMDAs are non-time deposits.) Alternatively, it implies that the CD rate is procyclically more flexible than the MMDA rate – if the bank is risk-averse.

A side issue in the above explanation is whether MMDAs and CDs are competed for on a local basis ($e_m < \infty$, $e_c < \infty$) or nationally ($e_m \approx \infty$, $e_c \approx \infty$). It is easily verified by rewriting equation (6) for $\Delta i_{c,t} - \Delta i_{m,t}$ that, even if $\gamma > 0$, $\Delta i_{c,t} = \Delta i_{m,t}$ arises if $e_m = e_c = \infty$. In this case, both the MMDA and CD rates move in tandem with the federal funds rate regardless of the bank's risk preference. Hence, for the explanation above to be persuasive, $e_m < \infty$ and $e_c < \infty$ need to be empirically supported. (The estimation of e_m and e_c is explained below in ESTIMATION RESULTS.)

EMPIRICAL SPECIFICATION AND A PAPER'S LIMITATION[10]

For the rest of the paper, the interest rate on two-period CDs is used: assume "c" = "c2" for the rest of the paper. The two-period CD rate in the theoretical model represents the six-month CD rate in the estimation.

For the second factor in equation (4), I assume the following approximation:

$$\log V_t \approx \mu + \varepsilon_t, \tag{7}$$

where μ = constant (and presumably $\mu > 0$)
ε_t = a stationary stochastic error.

Equation (7), or an approximation of the CD yield spread, is based on (a) an empirical regularity that the Treasury yield curve usually slopes upward [Mishkin, 2001] and (b) Treasury bill spreads are stationary due to cointegration between yields [Stock and Watson, 1988; Hall, Anderson, and Granger, 1992]. They suggest that $\log(V_t)$ may be described by the spread's equilibrium value (μ above which is likely positive according to (a)) plus a stationary stochastic error (ε_t above according to (b)).

Using equation (7), the empirical specification of equation (4) is expressed as

$$\begin{aligned} \log(i_{c,t}^{*}) - \log(i_{m,t}^{*}) &= -\alpha_c + \alpha_m - \log E_t(M_{t+1}) + \log V_t \\ &= -(\alpha_c - \mu) + \alpha_m - \xi_t \end{aligned} \tag{8}$$

where

$$\begin{aligned} \xi_t &\equiv \log E_t(M_{t+1}) - \varepsilon_t \\ &= \log\beta + \log E_t[(\pi_{t+1}/\pi_t)^{-\gamma}] - \varepsilon_t \ \text{(assuming the isoelastic utility function)} \\ &= \log\beta + E_t\log[(\pi_{t+1}/\pi_t)^{-\gamma}] + (k + \zeta_{t+1}) - \varepsilon_t \ \text{(assuming conditional lognormality)} \\ &= \text{constant} - \gamma\, E_t\log(\pi_{t+1}/\pi_t) + \text{error} \ \ (\text{constant} = \log\beta + k,\ \text{error} = \zeta_{t+1} - \varepsilon_t). \end{aligned} \tag{9}$$

The Jensen's inequality adjustment term on the third line of equation (9), $k + \zeta_{t+1}$, arises as follows. Assume that $(\pi_{t+1}/\pi_t)^{-\gamma}$ is conditionally lognormal, then $\log E_t[(\pi_{t+1}/\pi_t)^{-\gamma}] = E_t\log[(\pi_{t+1}/\pi_t)^{-\gamma}] + (1/2)\text{var}_t[\log(\pi_{t+1}/\pi_t)^{-\gamma}]$. Following Attanasio and Low [2000], assume $(1/2)\text{var}_t[\log(\pi_{t+1}/\pi_t)^{-\gamma}] \approx k + \zeta_{t+1}$ where k is a constant and ζ_{t+1} denotes a random component.

The paper's main objective is to estimate equations (8) and (9), or the CD-MMDA rate spread that ties the more flexible CD rate to the greater degree of risk aversion γ (the first factor) and the CD yield spread $\mu + \varepsilon_t$ (the second factor). It is done in two steps: first, estimate the time series of the unobserved variable ξ_t in equation (8) ("each city's CD – MMDA rate spread" below in ESTIMATION RESULTS) by the Kalman filter[11] and, second, estimate equation (9), or $\hat{\xi}_t$ = constant $- \gamma\, E_t\log(\pi_{t+1}/\pi_t)$ + error where $\hat{\xi}_t$ is the Kalman filter estimate of ξ_t ("individual banks' IMRS equations" below in ESTIMATION RESULTS).

Since the second factor ($\mu + \varepsilon_t$) is subsumed into a constant and an error in equations (8) and (9), it is not treated explicitly as an explanatory variable. This clearly limits the paper's investigation into the second factor. The error, ε_t, may possibly be autocorrelated and/or heteroskedastic, which will be taken into account in the estimation below.

DATA

For estimation, I use six cities' bank rates (MMDA rates and six-month consumer CD rates) that come from Bankrate.com (Bank Rate Monitor, Inc.). The sample period (monthly) is April 1986 (1986:4) through January 1997 (1997:1). The six cities are: 1 = New York, 2 = Chicago, 3 = San Francisco, 4 = Philadelphia, 5 = Detroit, 6 = Boston. Appendix A describes the data in more detail. Each city's MC (noninterest marginal cost of deposits or C_d) is estimated. Appendix B describes the details of the MC estimation.

ESTIMATION RESULTS

The following three sets of equations are estimated.

A. City j – city 1 MMDA rate differential (j = 2, 3, .., 6).
B. Each city's CD – MMDA rate spread or equation (8).
C. Individual banks' IMRS equations or equation (9).

The first set of equations (A) examines the side issue mentioned above, because whether banking markets and/or products are still local or not has been a much debated subject (see, for example, Rhoades [1992]; Radecki [1998]; Heitfield [1999]; Amel and Starr-McCluer [2002]; Heitfield and Prager [2002]). Also, as mentioned above, implied elasticity estimates are derived from the estimation results in order to support the explanation (the first factor) given above. The other two sets of equations (B and C) are explained above in connection with equations (8) and (9).

One complication that must be taken into account in the estimation of the three sets of equations is the rigidity of deposit rates found by Neumark and Sharpe [1992]. Following Neumark and Sharpe [1992], I assume the following partial adjustment model for both the CD and MMDA rates where the subscripts m and c are dropped for notational simplicity:

$$\Delta\log(i_t) = (\lambda + \delta DUM_t)\,[\log(i_t^*) - \log(i_{t-1})] + u_t, \qquad (10)$$

where $\Delta\log(i_t) = \log(i_t) - \log(i_{t-1})$
$DUM_t = 1$ if $i_t - i_{t-1} \geq 0$ and 0 otherwise
λ = downward adjustment speed ($\lambda > 0$)
$\lambda + \delta$ = upward adjustment speed (presumably $\delta < 0$).

Analogous to Neumark and Sharpe [1992], a random error u_t is added to the model. λ represents the degree of interest rate rigidity: the lower its value, the more rigid the interest rate is, reflecting banks' greater reluctance to adjust their interest rates. In addition, equation (10) takes account of asymmetric rigidity: if the rate is adjusted more slowly upward than downward, then $\delta < 0$.[12]

A. City j - City 1 MMDA Rate Differential (j = 2, 3, … , 6)

(11) $$\Delta\log(i_{j,t}) - \Delta\log(i_{1,t}) = (\lambda_j + \delta_j DUM_{j,t})[\log(i_{j,t}^*) - \log(i_{j,t-1})] - (\lambda_1 + \delta_1 DUM_{1,t})[\log(i_{1,t}^*) - \log(i_{1,t-1})] + \text{error}$$

where $i_{j,t}$, $i_{j,t}^*$ = city j's MMDA rate (j = 1, 2, 3, .., 6), omitting the subscript m
$\log(i_{j,t}^*) = -\alpha_j + \log(i_{f,t} - C_{d,j})$ (j = 1, 2, 3, .., 6)
$\alpha_j = \log(1 + e_j^{-1})$ (j = 1, 2, 3, .., 6)
e_j = city j's MMDA supply elasticity
$C_{d,j}$ = city j's MC (noninterest marginal cost) (j = 1, 2, …, 6)
error $= u_{j,t} - u_{1,t}$ (j = 2, 3, .., 6).

If MMDAs are local products, then the differential (the left-hand side of equation (11)) is characterized not by random variations but by local factors such as significant λ_j, δ_j, λ_1 and δ_1 (the right-hand side). The implied elasticity e_j is derived from the α_j estimate. A system of five equations (j = 2, 3,…, 6), nonlinear in the parameters and with cross-equation restrictions (α_1, λ_1 and δ_1 are the same across equations), is estimated by the method of SUR (seemingly unrelated regression).

The nonlinear SUR estimation results are shown in Table 1. (The details of the estimation procedure are available from the author upon request.) First, all parameter estimates are significant at the 0.1 percent level (except for one case where the estimate is significant at the 1 percent level) with the expected signs. Second, the statistical significance of all dummy variables bears out the finding of Neumark and Sharpe [1992] about the faster downward speed of adjustment.[13] Third, since changes in MMDA rate differentials between cities depend significantly on local factors (α_j's and λ_j's) and, also, the implied MMDA rate elasticity estimates range from 0.42 (Philadelphia) to 1.16 (Chicago), MMDAs are clearly not competed for at the national level, consistent with Berger and Hannan [1989] and Hannan and Liang [1993].

B. Each City's CD - MMDA Rate Spread or Equation (8) (Modified Based on Equation (10))

(12) $$\Delta\log(i_{c,t}) - \Delta\log(i_{m,t}) = (\lambda_c + \delta_c DUM_{c,t})[\log(i_{c,t}^*) - \log(i_{c,t-1})] - (\lambda_m + \delta_m DUM_{m,t})[\log(i_{m,t}^*) - \log(i_{m,t-1})]$$

where $DUM_{c,t} = 1$ if $i_{c,t} - i_{c,t-1} \geq 0$ and 0 otherwise, similarly for $DUM_{m,t}$
$\log(i_{m,t}^*) = -\alpha_m + \log(i_{f,t} - C_d)$
$\log(i_{c,t}^*) = -(\alpha_c - \mu) - \xi_t + \log(i_{f,t} - C_d)$
$\xi_t = \log E_t(M_{t+1}) - \varepsilon_t$.

The error term u_t in equation (10) is assumed to be the same for both the CD and MMDA equations for the same city and therefore drops out of the above equation. For the unobserved variable ξ_t in equation (12), the following is assumed.[14]

(13) $$\xi_t = F\xi_{t-1} + v_t$$

where F = constant

v_t = mean-zero Gaussian white noise with $E(v_t v_\tau) > 0$ if t = τ and 0 otherwise.

TABLE 1
City j – City 1 MMDA Rate Differential (j = 2, 3, …, 6), Nonlinear SUR Estimates, Monthly Sample 1986:5-1997:1

Equation (11): $\Delta\log(i_{j,t}) - \Delta\log(i_{1,t}) = (\lambda_j + \delta_j DUM_{j,t})[\log(i_{j,t}{}^*) - \log(i_{j,t\text{-}1})]$
$- (\lambda_1 + \delta_1 DUM_{1,t})[\log(i_{1,t}{}^*) - \log(i_{1,t\text{-}1})]$ + error,

where $\Delta\log(i_{j,t}) = \log(i_{j,t}) - \log(i_{j,t\text{-}1})$, $i_{j,t}$ = city j's MMDA rate
$\Delta\log(i_{1,t}) = \log(i_{1,t}) - \log(i_{1,t\text{-}1})$, $i_{1,t}$ = New York City MMDA rate
$\text{DUM}_{j,t} = 1$ if $i_{j,t} - i_{j,t\text{-}1} \geq 0$ and 0 otherwise (j = 1,2,…,6)
$\log(i_{j,t}{}^*) = -\alpha_j + \log(i_{f,t} - C_{d,j})$ (j = 1,2,…,6)
$\alpha_j = \log(1 + e_j^{-1})$ (j = 1,2,…,6)
e_j = city j's MMDA supply elasticity
$C_{d,j}$ = city j's noninterest marginal cost (j = 1, 2, …, 6)
(Each city's $C_{d,j}$ estimate is given in Appendix B.)
$i_{f,t}$ = federal funds rate.

	MMDA rate			
	Downward adjustment speed:		**Upward adjustment speed:**	
City	λ_j	δ_j	$\lambda_j + \delta_j$	α_j
New York (j = 1)	0.0549***	–0.0348***	0.0201	0.6545***
	(0.0099)	(0.0067)		(0.1271)
Chicago (j = 2)	0.0543***	–0.0244***	0.0299	0.6233***
	(0.0101)	(0.0051)		(0.1246)
San Francisco (j = 3)	0.0467***	–0.0225**	0.0242	0.8021***
	(0.0089)	(0.0080)		(0.2016)
Philadelphia (j = 4)	0.0232***	–0.0111***	0.0121	1.2255***
	(0.0062)	(0.0030)		(0.3409)
Detroit (j = 5)	0.0381***	–0.0231***	0.0150	0.7894***
	(0.0085)	(0.0056)		(0.1934)
Boston (j = 6)	0.0490***	–0.0347***	0.0143	0.6514***
	(0.0093)	(0.0079)		(0.1539)

Note: Standard errors are in parentheses.
*** Significant at the 0.1 percent level.
** Significant at the 1 percent level.

Equations (12) and (13), together called the state-space model, are estimated by maximum likelihood. The parameter estimates of λ_m, δ_m, and α_m (from the estimation of "city j – city 1 MMDA rate differential") are imposed. The implied elasticity e_c is derived from the α_c estimate. The time series of the unobserved variable ξ_t is estimated by the Kalman filter.

Table 2 shows the maximum likelihood estimates of the state-space model (equations (12) and (13)). (The details of the estimation procedure and identification are available from the author upon request.) The findings are similar to those in Table 1: most of the estimates are significant at the 0.1 percent level with the expected signs and (except for San Francisco) the significant δ_c estimates again bear out asymmetric adjustment. To be consistent with Neumark and Sharpe [1992], CD rates are much less rigid than MMDA rates (the values of λ_c and $\lambda_c + \delta_c$ are much larger than those of MMDA rates).[15]

TABLE 2
Each City's CD – MMDA Rate Spread (State-Space Model), Maximum Likelihood Estimates, Monthly Sample 1986:6-1997:1

Equation (12): $\Delta\log(i_{c,t}) - \Delta\log(i_{m,t}) = (\lambda_c + \delta_c DUM_{c,t})[\log(i_{c,t}{}^*) - \log(i_{c,t-1})]$
$\qquad -(\lambda_m + \delta_m DUM_{m,t})[\log(i_{m,t}{}^*) - \log(i_{m,t-1})]$

Equation (13): $\xi_t = F\xi_{t-1}$ + error

where $\Delta\log(i_{c,t}) = \log(i_{c,t}) - \log(i_{c,t-1})$, $i_{c,t}$ = CD rate
$\Delta\log(i_{m,t}) = \log(i_{m,t}) - \log(i_{m,t-1})$, $i_{m,t}$ = MMDA rate
$DUM_{c,t} = 1$ if $i_{c,t} - i_{c,t-1} \geq 0$ and 0 otherwise, similarly for $DUM_{m,t}$
$\log(i_{c,t}{}^*) = -(\alpha_c - \mu) - \xi_t + \log(i_{f,t} - C_d)$
$\log(i_{m,t}{}^*) = -\alpha_m + \log(i_{f,t} - C_d)$
$\xi_t \equiv \log E_t(M_{t+1}) - \varepsilon_t$ (See footnote 14.)
M_{t+1} = intertemporal marginal rate of substitution
$i_{f,t}$ = federal funds rate
C_d = noninterest marginal cost.
(Each city's C_d estimate is given in Appendix B.)

Parameters estimated: λ_c, δ_c, $\alpha_c - \mu$, F.
Time series estimated: ξ_t. (The resulting Kalman filter estimates $\hat{\xi}_t$ are used in Table 3.)
Parameter values imposed: λ_m, δ_m, α_m estimates from Table 1.

	CD rate				
	Downward adjustment speed:			Upward adjustment speed:	
City	λ_c	δ_c	$\lambda_c + \delta_c$	$\alpha_c - \mu$	F
New York	0.2331***	–0.0489***	0.1842	0.0723***	0.3876***
	(0.0243)	(0.0081)		(0.0155)	(0.1010)
Chicago	0.2014***	–0.0693***	0.1321	0.0646**	0.5726***
	(0.0256)	(0.0113)		(0.0241)	(0.0737)
San Francisco	0.2153***	–0.0084	0.2069	0.0694***	0.3977***
	(0.0142)	(0.0071)		(0.0129)	(0.0830)
Philadelphia	0.1235***	–0.0151***	0.1084	0.0265	0.5899***
	(0.0188)	(0.0038)		(0.0405)	(0.0636)
Detroit	0.1269***	–0.0430***	0.0839	0.1090**	0.2224*
	(0.0154)	(0.0060)		(0.0348)	(0.0929)
Boston	0.1193***	–0.0546***	0.0647	0.0515	0.2781**
	(0.0191)	(0.0087)		(0.0478)	(0.0830)

Note: Standard errors are in parentheses.
*** Significant at the 0.1 percent level.
** Significant at the 1 percent level.
* Significant at the 5 percent level.

The implied elasticity estimates derived from the α_c estimates are much larger than those of MMDA rates, consistent with the notion that CDs are competed for on a broader geographic basis [Berger and Hannan, 1989; and Hannan and Liang, 1993]. If $\mu = 0$ is assumed, then the implied CD rate elasticity estimates range from 8.68 (Detroit) to 18.92 (Boston), except for Philadelphia (37.23). The implied CD rate elasticity estimates are likely smaller, however, because μ is presumably positive.

Clearly, CDs are not competed for at the national level because these implied elasticity estimates vary widely from city to city, and their values are limited. Hence, the elasticity estimates (safely concluding $e_m < \infty$ and $e_c < \infty$) indeed provide support for the explanation of the first factor given above.

C. Individual Banks' IMRS Equations or Equation (9)

Equation (9) is estimated for selected individual banks in each city (Appendix B explains individual banks). Each city's time series estimates $\hat{\xi}_t$, which are obtained from the estimation of "each city's CD – MMDA rate spread" above and are interpreted as those of the city's representative bank, are used for ξ_t in equation (9) for individual banks in the same city. For the variable π_t, I use each individual bank's return on total assets (commonly denoted by ROA, that is, the ratio of net income to total assets) instead of each bank's net income because ROA data take into account mergers and/or acquisitions and/or divestitures while net income data do not.[16]

For unobserved $E_t\log(\pi_{t+1}/\pi_t)$ in equation (9), I assume two different expectation schemes. First, since ROA is likely stationary (see, for example, Bassett and Carlson, [2002, Table A.1]), one way to model expectations of such a stationary process is to assume regressive expectations: $E_t\log(\pi_{t+1}/\pi_t) = -\phi(\log\pi_t - \overline{\log\pi})$ where $\phi > 0$ and $\overline{\log\pi}$ denotes the long-run log(ROA) (for which the sample mean is used below). Second, I assume rational expectations: $\log(\pi_{t+1}/\pi_t) = E_t\log(\pi_{t+1}/\pi_t) + \omega_{t+1}$ where ω_{t+1} denotes an expectation error. Then, the empirical specifications of equation (9) based on regressive and rational expectations are, respectively, as follows.

$$\text{(14)} \qquad \text{Regressive Expectations: } \hat{\xi}_t = \text{constant} + \gamma\phi\left(\log\pi_t - \overline{\log\pi}\right) + \text{error}$$

$$\text{(15)} \qquad \text{Rational Expectations: } \hat{\xi}_t = \text{constant} - \gamma\log\left(\pi_{t+1}/\pi_t\right) + \text{error},$$

where constant $= \log\beta + k$

error $= \zeta_{t+1} - \varepsilon_t$ (equation (14)), and $\zeta_{t+1} - \varepsilon_t + \gamma\,\omega_{t+1}$ (equation (15)).

Several clarifications are necessary. First, since time series estimates of ξ_t are monthly while bank profit data are quarterly, simple averaging is used to convert monthly into quarterly series. Second, in actual estimation the regressors in equations (14) and (15) are lagged by one.[17] Third, equation (14) is estimated by OLS and IV (instrumental variable estimation).[18] IV is used because ε_t (possibly influenced by time-varying expectations on future monetary policy) may be correlated with the regressor (expected profit growth).[19] Equation (15) is estimated by IV because the regressor and the expectation error term (ω_{t+1}) are correlated. In addition, the regressor may be correlated with ε_t. Fourth, as indicated in connection with equations (7), (8) and (9), ε_t may possibly be autocorrelated and/or heteroskedastic. Therefore, the heteroskedasticity-autocorrelation consistent covariance matrix estimator [Newey and West, 1987] is used for statistical tests

The results are shown in Table 3.[20] Clearly, ξ_t is significantly associated with expected profit growth at the individual bank level (except for San Francisco) when regressive expectations are assumed. The results in Panel A (OLS estimates) show a

TABLE 3
Estimation Results of the RRA Coefficient (γ) of Individual Banks,[a] Quarterly Sample 1986:III-1997:I

Equation (14): $\hat{\xi}_t$ = constant+ $\gamma\phi\left(\log\pi_t - \overline{\log\pi}\right)$ + error

[Regressive Expectations, $E_t \log(\pi_{t+1}/\pi_t) = -\phi\left(\log\pi_t - \overline{\log\pi}\right)$, are assumed.]

Equation (15): $\hat{\xi}_t$ = constant$-\gamma\log\left(\pi_{t+1}/\pi_t\right)$ + error,

[Rational expectations, $\log(\pi_{t+1}/\pi_t) = E_t \log(\pi_{t+1}/\pi_t)$ + error, are assumed.]

where $\hat{\xi}_t$ = Kalman filter time-series estimates
π_t = ROA (return on assets)
$\overline{\log\pi}$ = long-run level (the sample mean is used).

Estimation methods: Equation (14) is estimated by OLS and IV (instrumental variable method). Equation (15) is estimated by IV. The instruments used for equation (14) (equation (15)) are four lags of the regressor of equation (15) (equation (14)). The validity of the instruments used is explained in footnote 18.

Note: For the actual estimation, the regressors in equations (14) and (15) are lagged by one (see footnote 17).

Equation (14)	Estimates[b] of $\phi\gamma$ ($\phi > 0$, $\gamma \geq 0$, γ = coefficient of relative risk aversion)					
	Bank 1	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**	**Bank 6**
			Panel A: OLS			
New York	0.0283*	0.0221**	–0.0063	0.0336**	–0.0007	0.0255*
	(0.0153)	(0.0108)	(0.0231)	(0.0165)	(0.0271)	(0.0155)
Chicago	0.3208***	0.2123***	0.1665***	0.2534***	0.1790***	
	(0.0492)	(0.0447)	(0.0334)	(0.0482)	(0.0518)	
San Francisco	0.0082	–0.0132	0.0130	–0.0086		
	(0.0253)	(0.0339)	(0.0228)	(0.0092)		
Philadelphia	0.1521***	0.1909**	0.2067***	0.1954**	0.0447**	
	(0.0376)	(0.0774)	(0.0681)	(0.0787)	(0.0211)	
Detroit	0.0890***	0.0248	0.0788**	0.0341*	0.0462*	
	(0.0220)	(0.0275)	(0.0312)	(0.0213)	(0.0257)	
Boston	0.1586***	0.0169**	0.0620	0.0563**		
	(0.0366)	(0.0080)	(0.0393)	(0.0284)		

little stronger evidence than those in Panel B (IV estimates). The finding is consistent with the theoretical interpretation of ξ_t as IMRS. Under the assumption of regressive expectations, the OLS point estimates of $\phi\gamma$ in Panel A that are statistically significant at least at the 10 percent level (two-tailed tests) range from 0.3208 to 0.0169 and their sample average is 0.1196. It implies that, for example, if $\phi = 0.9$ ($\phi = 0.5$), then the sample-average RRA coefficient is $\gamma = 0.1329$ ($\gamma = 0.2392$). Similarly, the IV estimates in Panel B that are statistically significant at least at the 10 percent level range from 0.3937 to 0.0333 and their sample average is 0.1862. If $\phi = 0.9$ ($\phi = 0.5$), then the sample-average RRA coefficient is $\gamma = 0.2069$ ($\gamma = 0.3724$).

Under the assumption of rational expectations, the finding is still consistent, though a little weaker, with the theoretical interpretation of ξ_t as IMRS. The point estimates of the RRA coefficient γ that are statistically significant at least at the 10

TABLE 3 — Continued
Estimation Results of the RRA Coefficient (γ) of Individual Banks,[a]
Quarterly Sample 1986:III-1997:I

Equation (14)	Estimates[b] of $\phi\gamma$ ($\phi > 0$, $\gamma \geq 0$, γ = coefficient of relative risk aversion)					
	Bank 1	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**	**Bank 6**
	Panel B: IV (Instrumental variable)					
New York	0.0523***	0.0221	0.0333*	0.2194**	–0.0078	0.1072*
	(0.0116)	(0.0153)	(0.0207)	(0.1029)	(0.0355)	(0.0603)
Chicago	0.3091***	0.2718***	0.1888**	0.2673***	0.1287**	
	(0.0574)	(0.1033)	(0.0749)	(0.0789)	(0.0615)	
San Francisco	–0.0440	–0.0878	0.0314	–0.0106		
	(0.0918)	(0.0883)	(0.0322)	(0.0115)		
Philadelphia	0.1236***	0.1754	0.3937*	0.2386	0.2700***	
	(0.0407)	(0.1837)	(0.2315)	(0.1639)	(0.1027)	
Detroit	0.1137***	–0.0101	0.0795	–0.0042	0.0137	
	(0.0434)	(0.0113)	(0.0617)	(0.0244)	(0.0204)	
Boston	0.1643***	0.1505***	–0.0068	0.0271		
	(0.0497)	(0.0544)	(0.0404)	(0.0803)		

Equation (15)	Estimates[b,c] of $-\gamma$ ($\gamma \geq 0$, γ = coefficient of relative risk aversion)					
	Bank 1	**Bank 2**	**Bank 3**	**Bank 4**	**Bank 5**	**Bank 6**
New York	–0.0371*	–0.0225	–0.0975	–0.1601**	0.0179	–0.0352
	(0.0214)	(0.0164)	(0.1974)	(0.0757)	(0.0222)	(0.0861)
Chicago	–0.3733*	–0.9655*	–0.1124	–0.9801	–0.3503	
	(0.1942)	(0.5132)	(0.1294)	(0.7225)	(0.3108)	
San Francisco	0.0141	0.1093	–0.0016	0.0130		
	(0.1097)	(0.0851)	(0.0245)	(0.0128)		
Philadelphia	–0.1455**	–0.5339	1.3239	–0.3089*	–0.2248	
	(0.0677)	(0.5390)	(1.3374)	(0.1804)	(0.4330)	
Detroit	–0.3211	–0.0171	–0.0591	–0.0258	–0.0617	
	(0.2631)	(0.0347)	(0.1221)	(0.0290)	(0.0779)	
Boston	–0.2190***	–0.1162*	–0.0113	–0.1152		
	(0.0458)	(0.0652)	(0.0356)	(0.1112)		

Note: Standard errors are in parentheses.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.
a Appendix B explains individual banks for each city.
b The heteroskedasticity-autocorrelation consistent covariance matrix estimator is used [Newey and West, 1987].
c Instrumental variable estimation.

percent level (two-tailed tests) range from 0.9655 to 0.0371 (from 0.3733 to 0.0371 if Chicago-Bank 2 is excluded) and their sample average is 0.2907 (0.1943 if Chicago-Bank 2 is excluded).

Based on the estimates in Table 3, the individual banks' RRA coefficients appear to fall between 0 and 1 (most likely around 0.2) and hence banks are risk-averse. However, the estimates in this paper are very close to zero, suggesting that banks may be nearly risk-neutral. The range of the RRA coefficient estimates is consistent with $\gamma \approx 1$, or $\gamma < 2$, or $\gamma < 3$, which economists commonly agree on [Arrow, 1965; Ljungqvist and Sargent, 2000, 258-260; Feldstein and Ranguelova, 2001]. One implication for equation (8) from the finding of near risk-neutrality is that, although the first factor (the $\gamma E_t \log(\pi_{t+1}/\pi_t)$ term) indeed explains the observed relative flexibility of CD rates, its quantitative importance to account for the CD-MMDA rate spread may be limited because $\gamma \approx 0$.[21] This of course does not diminish the importance of the paper's main objective of investigating whether banks are risk-averse or not.

Lastly, it is noted that insignificant results in Table 3 are difficult to interpret because they may arise, even if the theoretical interpretation of ξ_t as IMRS is true, when any of the auxiliary assumptions (such as isoelastic utility and the lognormal distribution) is empirically invalid at the individual bank level.

CONCLUSION

I have analyzed an issue which has received little attention in the literature: whether or not, and to what extent, banks are risk-averse. Based on an intertemporal bank model, I have shown that IMRS (intertemporal marginal rate of substitution), or indirectly the RRA (relative risk aversion) coefficient, explains a fundamental difference between the interest rates on time deposits (CDs) and non-time deposits (MMDAs). In particular, the greater degree of procyclical flexibility in the CD rate (than the MMDA rate) is associated with the greater degree of risk aversion. I have estimated the hypothesized relationship between IMRS and the RRA coefficient at the individual bank level, where the unobservable IMRS in the CD-MMDA rate spread is estimated using the Kalman filter. The individual banks' RRA coefficients appear to fall between 0 and 1 (most likely around 0.2), thereby providing evidence that banks are risk-averse, though close to being risk-neutral.

APPENDIX A

Data

Monthly data for the MMDA rate and the six-month consumer CD rate, April 1986 (1986:4) through January 1997 (1997:1), come from Bankrate.com (Bank Rate Monitor, Inc). which is the same data source used previously by others [Diebold and Sharpe, 1990; Radecki, 1998; Heitfield, 1999]. Longer and consistent time-series data are available for ten major markets. Out of these ten markets, I exclude four markets (Los Angeles, Houston, Dallas and the District of Columbia), leaving six markets (j = 1, 2, … , 6) to be analyzed in this paper: New York (j = 1), Chicago (j = 2), San Francisco (j = 3), Philadelphia (j = 4), Detroit (j = 5), and Boston (j = 6). The out-of-state bank holding companies' deposit shares in the District of Columbia and Texas were, respectively, 58.70 percent and 53.01 percent in June, 1993 [Savage, 1993], suggesting that the District of Columbia, Houston and Dallas do not constitute geographically well-defined local markets for deposits. A close examination of Los Angeles and San Francisco data indicates that these cities' data are practically identical, hence excluding Los Angeles. The sample starts from 1986:4 because the data are not available before that for San Francisco and Boston. The sample ends at 1997:1, covering the period of interstate (and intrastate) banking restrictions that had effectively limited the scope of geographic expansion of banking activities in the United States [Savage, 1987; 1993]. I focus on this period in order to maintain the analysis free from the nationwide banking era that has started effectively in 1997 under the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. Each city's deposit rate used in this paper is calculated (by Bankrate.com) as the simple average of the city's ten large institutions' deposit rates (five large banks and five large thrifts) which is interpreted as the deposit rate of a representative (or an average) bank in that city. The monthly federal funds rate data come from DRI/McGraw-Hill (RMFEDFUNDSNS series).

APPENDIX B

MC Estimation

Since monthly deposit rate data are averages of ten large institutions' rates for each city, it is reasonable to base each city's MC estimation on these ten institutions which can be identified in *Bank Rate Monitor* published by Bankrate.com. Because of mergers/acquisions over time and/or incomplete data availability for some banks, each city ends up with only about five banks that have complete data for estimation. The table below shows the names of banks included in the MC estimation and for which equations (14) and (15) are estimated.

The procedure to obtain MC estimates is as follows. First, using 1986:III-1997:I quarterly data (from the Federal Reserve Bank of Chicago BHC database), I estimate the standard translog noninterest cost function with the symmetry and homogeneity restrictions, which is based on Gilligan, Smirlock, and Marshall [1984], for individual banks that were included in the Bankrate.com survey list (below). Second, MC estimates for 1986:III-1997:I of individual banks are derived from the estimated translog cost functions. Third, constant MC for a representative bank for each city is calculated as the average of sample means of (each city's) individual bank's MCs weighted by each bank's 1994 MSA deposit share. Further details are available from the author upon request. The results are: 0.00311 (San Francisco) < 0.00441 (Chicago) < 0.00531 (New York) < 0.00802 (Detroit) < 0.00919 (Boston) < 0.01153 (Philadelphia). (For San Francisco, MC = 0.00311 means that the marginal noninterest operating costs are $0.00311 per total deposits dollar.)

Banks surveyed by Bankrate.com (Bank Rate Monitor, July 24, 1996)

New York

Chase Manhattan Bank (Bank 1), Bank of New York (Bank 2), Citibank (Bank 3), Emigrant Savings (Bank 4), Green Point Bank (Bank 5), Republic National Bank (Bank 6).

Chicago

Harris Trust & Savings Bank (Bank 1), Northern Trust Bank (Bank 2), First National Bank Chicago (Bank 3), American National B & T (Bank 4), LaSalle National Bank (Bank 5).

San Francisco

Bank of America (Bank 1), Wells Fargo Bank (Bank 2), Sumitomo Bank of California (Bank 3), Union Bank (Bank 4).

Philadelphia

CoreStates Bank (Bank 1), Mellon Bank (Bank 2), Beneficial Mutual Savings Bank (Bank 3), Frankford Bank (Bank 4), Firstrust Savings Bank (Bank 5).

Detroit

NBD Bank (Bank 1), First of America Bank (Bank 2), Michigan National Bank (Bank 3), Huntington Banks of Michigan (Bank 4), Comerica Bank (Bank 5).

Boston

Fleet Bank of Massachusetts (Bank 1), Cambridge Savings Bank (Bank 2), US Trust (Bank 3), PNC Bank New England (Bank 4).

NOTES

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1. Duration (denoted by d), due to Macaulay [1938], measures the average maturity of a security's stream of future cash flows and is defined by $d \equiv \sum_{t=1}^{T} \left[tCF_t /(1+i)^t \right] / P$ where CF_t denotes the cash flow in period t, i denotes the discount rate, and P denotes the present value of future cash flows of the security. Duration gap management is explained in, for example, Rose [2002].
2. Ratti [1980] shows evidence of banks' risk aversion based on a static stochastic bank model and using 1976-77 pre-deregulation data (i.e., prior to the elimination of Regulation Q interest-rate ceilings). Angelini [2000] also shows evidence of banks' risk aversion based on the finding that Italian banks' intraday interbank operations are more concentrated in early morning hours on settlement days, which is consistent with the risk-averse assumption in his theoretical model.
3. "A price change instituted on CDs affects only marginal accounts – new CDs issued or old ones rolled over – and represents a contractual commitment. In contrast, for MMDAs, a change in price amounts to a repricing of all accounts, and confers no explicit contractual commitment on yields even one week into the future" [Neumark and Sharpe, 1992, 677].
4. More precisely, $d_A - (MVL/MVA)d_L > 0$ where MVL and MVA are the market value of liabilities and the market value of assets, respectively.
5. I thank a referee for pointing out the term structure of interest rates.
6. It is assumed that the federal funds rate is an indicator of monetary policy [Bernanke and Blinder, 1992].
7. $\log E_t(M_{t+1}) > E_t \log(M_{t+1})$.
8. The federal funds rate is known to be procyclical [Stock and Watson, 1999].
9. The first order condition with respect to ι_t is: $\iota_t^* = (1 - e_l^{-1})^{-1} E_t(M_{t+1})^{-1}(i_{f,t} + C_l)$ where $e_l = -(\iota_t/L_t)(\partial L_t / \partial \iota_t)$. Therefore, ι_t^* also changes (in addition to changes in $i_{c,t}^*$ and $i_{m,t}^*$) when $i_{f,t}$ changes.
10. The full version of this paper, available from the author upon request, addresses two additional possible limitations: the absence of the household's decision in this paper, and the assumption of constant MC.
11. The variable ξ_t includes unobserved conditional expectations $E_t(M_{t+1})$. I follow, for example, Fama and Gibbons [1982] and Hamilton [1985] who use the Kalman filter method [Hamilton, 1994] for unobserved conditional expectations.
12. Neumark and Sharpe [1992] primarily focus on deposit rate rigidity measured by the estimate of λ and its determinants, whereas this paper's primary interest (with secondary interest in the λ estimates) is in the optimal deposit rate i_t^* which (together with λ) accounts for the observed sluggishness of the actual deposit rate i_t relative to open market rates (such as $i_{f,t}$).

13. The full version of this paper discusses differences between the estimates of λ in Neumark and Sharpe [1992] and those in this paper.
14. In actual estimation, the state variable is defined as $(\lambda_c + \delta_c DUM_{c,t})\xi_t$ (instead of ξ_t). After λ_c, δ_c and the state variable are estimated, $\hat{\xi}_t$ is derived by $\hat{\xi}_t$ = (state variable estimate) $\left(\hat{\lambda}_c + \hat{\delta}_c DUM_{c,t}\right)^{-1}$ where the hat ^ indicates the estimate.
15. One possible explanation of greater MMDA rate rigidity, not explained in Neumark and Sharpe [1992], is that bank customers holding MMDAs may be less attentive to rate fluctuations than CD holders. Hence, banks may change MMDA rates less frequently. This was pointed out by a referee.
16. Quarterly data of individual banks' net income and total assets come from the Federal Reserve Bank of Chicago BHC database.
17. The time series data of $\hat{\xi}_t$ (the regressand) estimated by the Kalman filter are one-step ahead conditional forecasts of ξ_t, that is, $\hat{\xi}_{t|t-1}$. On the other hand, the regressor is $E_t\log(\pi_{t+1}/\pi_t)$. To match the time subscripts (because, by definition, $\xi_t \equiv \log E_t(M_{t+1}) - \varepsilon_t$), the regressor is lagged by one. (The full version of this paper explains this in a little more detail).
18. For equation (14) (for equation (15)), four lags of the regressor in the other equation, i.e., equation (15) (equation (14)), are used as instruments. For the chosen instruments, I tested the null hypothesis of independence of the instruments and the error term using the Sargan's instrument validity test [Cuthbertson, Hall, and Taylor, 1992] at the 5 percent significance level. For equation (14), only 4 cases out of 29 tests (29 banks) resulted in rejection of the null, suggesting validity of the instruments used. For equation (15), there were 7 rejections (out of 29 tests), suggesting a little weaker, nevertheless likely support of, validity of the instruments used. The instruments used appeared reasonably correlated with the regressor. The average of 58 sample correlations (29 correlations from each of equations (14) and (15)) between the regressor and the instruments was about 0.6. Therefore, the instruments chosen are considered reasonably valid.
19. I thank a referee for pointing out this correlation.
20. The sample period is 1986:III-1997:I for most banks; however, it is shorter for some banks (Bank 4 and Bank 5 of New York; Bank 3 and Bank 5 of Philadelphia) due to only partial availability of net income data. Also, each of the following three banks' samples includes one undefined observation for the regressor (i.e., $\log\pi$ is undefined) due to a non-positive value of π = ROA: Detroit Bank 3 (1995:IV); Detroit Bank 5 (1987:IV); and Boston Bank 4 (1993:III). Based on Greene [1993, 273-276], I drop this one observation from each bank's sample.
21. I thank a referee for mentioning this important point.

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