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Post-Deregulation Bank-Deposit-Rate Pricing: The Multivariate Dynamics

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The relationship between wholesale and retail interest rates since deregulation is of substantial interest to economists and policymakers, because the predictability of the monetary aggregates and their relationship to bank reserves depend on adjustment patterns in the wholesale and retail money markets. We provide evidence on the nature of wholesale–retail interest rate relationships by examining the dynamic interactions among two wholesale interest rates (federal funds and six-month treasury bills) and three retail deposit rates (six-month consumer certificates of deposit, money market deposit accounts, and super NOW's). We perform a multivariate time series analysis, with particular attention paid to causal patterns and the shapes of impulse-response functions. A number of stylized facts, related to size of adjustment, speed of adjustment, and pattern of adjustment, are established for the response of retail rates to unanticipated shocks in wholesale rates.

KEY WORDS: Causality; Cointegration; Dynamic model specification; Money market; Unit root; Vector autoregression.

1. INTRODUCTION

The use of money as an indicator of aggregate output movements is predicated on the presumption of stable demand elasticities for liquid balances. The removal of deposit interest ceilings in the early 1980s, however, has left liquid-asset demands sensitive to the vagaries of deposit interest rate adjustment. Consequently, as long as policymakers continue to use (or are perceived to use) monetary aggregates as instruments or indicators, the relationships between market and retail deposit interest rates will be a continuing concern.

The velocity of the monetary aggregates has always been sensitive to the opportunity costs of holding their component assets. Prior to deregulation, these opportunity costs were simply a function of the level of market interest rates. Since the retraction of Regulation Q ceilings, however, portfolio allocations among assets of varying liquidity have become dependent as well on bank-deposit repricing practices. Temporary changes in spreads between open-market interest rates and retail deposit interest rates have thus substantially complicated the short-term indicator properties of the aggregates. Different response magnitudes among retail deposit rates to fluctuations in banks' wholesale funding costs imply different opportunity-cost movements. Unpredictability in the timing of retail-deposit interest-rate responses further detracts from the practicality of using the monetary aggregates for policy purposes.

Although the modeling of opportunity-cost dynamics has received some attention in the Federal Reserve's M1 and M2 forecasting model (see Moore, Porter, and Small 1988), it is surprising that wholesale–retail interest rate interaction has received so little attention in the academic literature. In this article, we take a step toward rectifying this situation by examining the multivariate dynamics of three retail deposit rates and two wholesale deposit rates in the context of a five-dimensional vector autoregression. We address the following questions, among others:

1. What are the causal patterns, if any, between retail and wholesale interest rates?
2. How much of unanticipated movements in the various wholesale rates will eventually be reflected in the various retail rates?
3. How quickly, and with what patterns, do retail rate adjustments occur?
4. Do shocks to the various wholesale rates induce similar retail rate responses, or do retail ratesetters pay more attention to certain wholesale rates?
5. What are the dynamics of the changes in spreads, or opportunity costs, following unanticipated movements in the various wholesale rates?
6. Are adjustment magnitudes, speeds, and patterns roughly the same for all retail rates, or do substantial differences exist?

We proceed as follows. In Section 2, we describe our interest-rate data and examine them graphically. To motivate the specification adopted, we also discuss issues related to stationarity, unit roots, and cointegration. In Section 3, we examine bivariate and multivariate causal patterns. In Section 4, we study the moving average representation of the system; the shapes of impulse-response functions are given particular attention. Section 5 contains extended discussion, and Section 6 concludes.

2. DATA DESCRIPTION

The three retail deposit interest rates examined in this article are the six-month consumer certificate of deposit (CD) rate (6MCD), the money market deposit account rate (MMDA), and the super NOW (SN) rate. The retail rate data are taken from the *Bank Rate Monitor*. Each retail rate is an average of retail rates reported by 25 major commercial banks and 25 major thrifts and is expressed as an effective annual yield. The retail rates are reported by institutions every Wednesday.

The corresponding Wednesday wholesale rates are taken from the Federal Reserve Board's data base. We examine the six-month treasury bill (6MTB) rate and the federal funds (FF) rate, expressed in terms of effective annual yields. Preliminary analysis also included the six-month jumbo CD rate, but because its statistical properties were found to be nearly indistinguishable from those of the treasury bill rate, it was dropped from the analysis.

The sample period is October 5, 1983–December 25, 1985. The starting date corresponds to the removal of rate ceilings on all time deposits, the last of which was removed on October 1, 1983. The ending date coincides with the January 1, 1986, elimination of the regulatory distinction between super NOW accounts and NOW accounts and minimum-balance requirements on time deposits. (Prior to 1986, both NOW's and super NOW's were essentially transaction accounts; super NOW accounts faced no interest restrictions, however, and were subject to minimum-balance requirements, whereas NOW accounts were subject to a 5.25% rate ceiling but no minimum-balance requirements.) Our study thus focuses on a period during which deposit regulations were relatively stable.

The effective annual wholesale and retail yields are plotted together in Figure 1. They tend to move together; all climb until mid-1984, followed by a downward drift, which is briefly interrupted in early 1985. The comparatively high variability of the FF rate is evident. Moreover, 6MTB and 6MCD appear to move together fairly closely; both fluctuate more than SN and MMDA but less than FF. Overall, the wholesale rates seem to lead somewhat. There appears to be a lead progressing from FF to 6MTB, to 6MCD, MMDA, and SN, with a corresponding progression of decreasing volatility.

For both theoretical and empirical reasons, there is little reason to be concerned with trend or drift in the data. The prospect of a long-run pattern of consistent interest rate increases (or decreases) is unattractive on a priori grounds. Moreover, inclusion of a trend in the

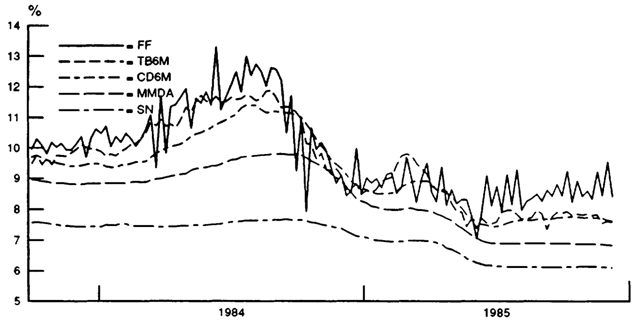

Figure 1. Effective Annual Yields.

subsequent empirical analysis of interest rate levels (or drift terms in the case of differenced data) is consistently inconsequential; estimated trends and drifts are economically small and statistically insignificant.

The issue remains, however, as to whether the interest rates are best characterized as stationary or integrated and, if they are integrated, whether common unit roots (i.e., cointegrating relationships) exist. These matters are important, subtle, and difficult to resolve. [See Diebold and Nerlove (1989) for a survey of the relevant literature.] Fortunately, many of the questions in which we are interested may be answered by analyzing the data in levels, regardless of whether the data are stationary, integrated, or cointegrated. In all cases, point estimates garnered via the analysis in levels are consistent; furthermore, as shown by Sims, Stock, and Watson (1988), their rate of convergence is typically faster when unit roots are present. Consequently, the primary analysis of this article (Secs. 3 and 4) is performed on levels data. In Section 5, we perform a robustness check by comparing the levels results with those arising from systems in which integration or cointegration is explicitly imposed.

When formal inference is required, such as in tests of causality and exogeneity, proper statistical characterization of the data is more important, because the presence of unit roots generally requires the use of nonstandard asymptotic distribution theory. Inference on the levels system is performed in Sections 3 and 4 under the assumption that the levels data are stationary. In Section 5, as a robustness check, the alternative inference appropriate for an integrated system is performed.

3. BIVARIATE CAUSAL PATTERNS

To gain some preliminary insights into the nature of the temporal relationships among the various retail and wholesale rates, we perform a pairwise series of causality tests. The analysis is of direct informational value in assessing the nature of interaction among rates and is a logical precursor to the multivariate causality and block exogeneity tests performed subsequently. The phrase "x causes y," as used here, means that x contains useful information for predicting y, in the linear least squares sense, over and above the past history of y.

Our priors as to the structure of causality are of mixed precision. We strongly expect one-way causality to run from wholesale rates to retail rates. Unless banks anticipate movements in wholesale rates based upon information not contained in those rates, and quickly adjust their rates on retail accounts in response to those anticipations, wholesale rate movements should contain information useful for predicting retail rates, but not vice versa. Among wholesale rates, it is expected that the fed funds rate would cause movements in the treasury bill rate, since shifts in supply of, and demand for, loanable funds tend to originate in the fed funds market. On the other hand, since treasury securities are used in open-market operations, innovations in their yields may provide useful information in predicting the fed funds rate.

The causality structure among our retail rates is likely to be less clear-cut. Among the retail rates, we expect super NOW to respond most slowly to wholesale rate movements; thus the other retail rates are likely to cause super NOW. Although this presumption is certainly influenced by casual observation, it is also supported by economic reasoning. The super NOW is primarily a transactions account, with important utility- and cost-bearing characteristics aside from its yield. Furthermore, it is relatively costly for owners to switch their super NOW account from institution to institution, which makes price-smoothing a feasible, and perhaps cost-effective, device for allocating economic surplus.

Finally, both money market deposit accounts and six-month consumer CD's are insured savings vehicles. Although used as such, MMDA's are instantaneous maturity assets, providing limited transaction services as well. Like the super NOW, all of a bank's MMDA funds are repriced when the offered yield changes. In contrast, a change in the offered yield on CD's immediately impacts only on newly issued CD's and those being rolled over, since the rate on already-issued deposits is locked in. Price smoothing may thus be more feasible for MMDA's than for CD's, and competing banks may react less to potentially short-term movements in interest rates when pricing MMDA's as compared to CD's. For these reasons, it is reasonable to posit 6MCD as causally prior to MMDA.

Consider the bivariate autoregressive moving average (ARMA) representation

$$\Phi(L)r_t = c + \Theta(L)\varepsilon_t. \quad (1)$$

Writing this out, we have

$$\begin{bmatrix} \phi_{11}(L) & \phi_{12}(L) \\ \phi_{12}(L) & \phi_{22}(L) \end{bmatrix} \begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \theta_{11}(L) & \theta_{12}(L) \\ \theta_{21}(L) & \theta_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \quad (2)$$

where all of the ϕ polynomials in the lag operator are of degree p and all θ polynomials are of degree q. Granger's (1969) test for causality is based on the (possibly infinite) autoregressive representation

$$\Theta^{-1}(L)\Phi(L)r_t = A(L)r_t = c\Theta^{-1}(1) + \varepsilon_t, \quad (3)$$

where

$$A(L) = \begin{bmatrix} a_{11}(L) & a_{12}(L) \\ a_{21}(L) & a_{22}(L) \end{bmatrix} \quad (4)$$

We say that r_2 does not cause r_1 iff $a_{12} = 0$. Similarly, we say that r_1 does not cause r_2 iff $a_{21} = 0$.

The results of the causality tests are given in Table 1. Each entry represents the marginal significance level (p value) at which one can reject the hypothesis that the row variable (r_i) does not cause the column variable (r_j). In other words, the null hypothesis is that $(\gamma_1, \gamma_2, \ldots, \gamma_p) = 0$ in the regression

$$r_{jt} = c_j + \beta_1 r_{j,t-1} + \cdots + \beta_p r_{j,t-p} + \gamma_1 r_{i,t-1} + \cdots + \gamma_p r_{i,t-p}. \quad (5)$$

The results presented are for $p = 5$ lags. The results are ordered such that, if the causal relationships conform to our priors, below-diagonal p values would be small. If, in addition, there does not exist feedback from retail to wholesale rates, most of the above-diagonal entries should be larger.

The data are generally consistent with our expectations. Consider first the major intergroup blocks underlined in the tables. The conjecture that wholesale rates cause retail deposit rates is confirmed; we observe small p values in the underlined blocks below the diagonal. Moreover, there appears to be little feedback from retail to wholesale rates, as indicated by the generally large p values in the upper underlined blocks. One exception is the apparent causal link from MMDA to 6MTB.

The remaining p values (not underlined) correspond to intra-retail and intra-wholesale causal patterns. They also generally correlate with our priors; all of these below-diagonal entries are less than .02, whereas two of these three above-diagonal entries are greater than .13. One exception is the apparent feedback from SN to 6MCD.

Table 1. Bivariate Interest Rate Causal Patterns, Levels Data, Five Lags

	r_j				
r_i	SN	MMDA	6MCD	6MTB	FF
SN	—	—	.02	<u>.55</u>	<u>.26</u>
MMDA	.02	—	.17	<u>.04</u>	<u>.18</u>
6MCD	.02	.01	—	<u>.43</u>	<u>.15</u>
6MTB	<u>.01</u>	<u>.00</u>	<u>.00</u>	—	.08
FF	<u>.08</u>	<u>.01</u>	<u>.01</u>	.00	—

NOTE: Entries are p values for the null hypothesis that interest rate r_i does not cause interest rate r_j, using five lags of r_i and r_j. Intergroup blocks are underlined.

4. VECTOR AUTOREGRESSIONS

4.1 Order Estimation

We first find a finite-ordered vector autoregressive approximation to the dynamics of our five-variable system, (FF, 6MTB, 6MCD, MMDA, SN). We consider four information-theoretic model-selection criteria due to Akaike (1969) [final prediction error criterion (FPEC)], Akaike (1974) [Akaike information criterion (AIC)], Schwarz (1978) [Schwarz information criterion (SIC)], and Hannan and Quinn (1979) [Hannan–Quinn information criterion (HQC)]. If $\Theta(L) = 0$, so that the true model is in fact a pth-order vector autoregression [VAR(p)], and if the order of the true model is not greater than the maximum order considered, then the SIC and HQC, but not the AIC, are consistent; that is, SIC and HQC asymptotically select the correct model with probability 1. On the other hand, if no finite-ordered VAR representation exists, AIC and FPEC provide asymptotically minimum mean squared prediction error approximations, as shown by Shibata (1980). Asymptotically, AIC and FPEC lead to selection of the same model, because $\ln \text{FPEC}(p) = \text{AIC}(p) + O(1/T)$, as shown by Lütkepohl (1985).

Because the different model-selection criteria have different optimality properties under circumstances that cannot be ascertained a priori, we report the results for each of them, defined as

$$\text{AIC}(p) = \ln|\hat{\Sigma}_p| + (2/T)d^2p, \qquad (6)$$

$$\text{SIC}(p) = \ln|\hat{\Sigma}_p| + (\ln T/T)d^2p, \qquad (7)$$

$$\text{FPEC}(p) = |\hat{\Sigma}_p|[(T + pd + 1)(T - pd - 1)], \qquad (8)$$

and

$$\text{HQC}(p) = \ln|\hat{\Sigma}_p| + (2 \ln \ln T/T)d^2p, \qquad (9)$$

where T is sample size, p is the order of the estimated VAR, $\hat{\Sigma}$ is the estimated innovation covariance matrix, and d is the dimension of the VAR.

The results are shown in Table 2. No criterion selects a model of order greater than 2; the AIC, FPEC, and HQC select a VAR(2), and SIC selects a VAR(1). That the lowest-dimensional model should be selected by SIC is unsurprising, since it incorporates the strongest penalty for degrees of freedom used. In light of the likely superior approximation properties of AIC and FPEC under misspecification, and to maintain conservatism, we adopt the VAR(2) specification.

Table 2. Criteria for VAR Lag-Length Selection, Levels Data

Model selection criteria	Model				
	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
AIC	−25.34	<u>−25.94</u>	−25.90	−25.68	−25.74
SIC	<u>−24.74</u>	−24.72	−24.08	−23.26	−22.71
ln FPE	−25.25	<u>−25.85</u>	−25.80	−25.57	−25.61
HQC	−25.10	<u>−25.45</u>	−25.16	−24.70	−24.51

NOTE: The model selected by each criterion is underlined.

4.2 Model Estimation, Multivariate Causality, and Block Exogeneity

We now report estimation and testing results for our five-dimensional model:

$$\begin{bmatrix} \phi_{11}(L) & \cdots & \phi_{15}(L) \\ \vdots & & \vdots \\ \phi_{51}(L) & \cdots & \phi_{55}(L) \end{bmatrix} \begin{bmatrix} r_{1t} \\ \vdots \\ r_{5t} \end{bmatrix} = \begin{bmatrix} c_1 \\ \vdots \\ c_5 \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{5t} \end{bmatrix} \qquad (10)$$

where r_1 = FF, r_2 = 6MTB, r_3 = 6MCD, r_4 = MMDA, r_5 = SN, and the degree of all $\phi(L)$ polynomials is 2. Because the same regressors appear in each equation, the model is efficiently estimated by least squares. As is common, however, the VAR parameter estimates are difficult to interpret directly. For this reason, we follow standard practice and focus on variance decompositions and impulse-response functions.

Table 3 contains the results from exclusion tests, the multivariate analog of our earlier bivariate causality analyses, which test for the exclusion of all lags of r_j from the r_i equation (for each $i, j, i \neq j$). Although they generally concur with the bivariate results, there are some interesting departures. As before, below-diagonal p values tend to be small, but those above the diagonal tend to be large. One particularly interesting departure is the rejection of marginal explanatory power from each of the wholesale rates to super NOW; FF and 6MTB provide no additional predictive power once the lagged behavior of 6MCD and MMDA is accounted for. Similarly, 6MCD displays no marginal predictive power with respect to the behavior of MMDA. Notable also is the finding that both MMDA and 6MCD have marginal predictive power with respect to 6MTB movements, even with the past behavior of FF accounted for.

It is also of interest to test the block exogeneity of all wholesale rates with respect to deposit rates, the null hypothesis being that $\phi_{13}(L) = \phi_{14}(L) = \phi_{15}(L) = \phi_{23}(L) = \phi_{24}(L) = \phi_{25}(L) = 0$. The likelihood-ratio test statistic for this hypothesis assumes a value of 23.7, distributed as $\chi^2(12)$ under the null hypothesis (since each ϕ polynomial is of degree 2); it is significant at the 2.2% level. Thus the block exogeneity of wholesale rates with respect to deposit rates is rejected at conventional levels, a likely reflection of the apparent feed-

Table 3. Multivariate Interest Rate Causal Patterns, Levels Data

r_i	r_j				
	SN	MMDA	6MCD	6MTB	FF
SN	—	.35	.66	.97	.95
MMDA	.01	—	.71	.06	.82
6MCD	.04	.39	—	.02	.92
6MTB	.74	.00	.00	—	.12
FF	.54	.00	.00	.01	—

NOTE: Entries are p values for the null hypothesis that interest rate r_i does not cause interest rate r_j, using two lags of all five interest rates.

back from retail rates to 6MTB. We therefore do not impose the zero restrictions in the analysis that follows.

4.3 Variance Decompositions

Both variance decompositions and impulse-response functions are generated by analyzing the effects of unanticipated shocks in the vector moving average representation of the vector autoregressive system. The Choleski factor, $\hat{G}$ (where $\hat{\Sigma} = \hat{G}\hat{G}'$), is used to normalize the system so that the transformed innovation covariance matrix is diagonal, thereby allowing us to consider experiments in which any rate or set of rates is independently shocked. Since a change in the ordering of equations alters the Choleski factor, the conclusions one may draw are potentially sensitive to the normalization, or ordering, chosen. Intuitively, the ordering determines how much of the contemporaneously correlated part of the shocks to the system is attributed to each of the system variables. For example, because the FF rate is ordered first in our analysis, the part of the shock to the FF rate that is correlated (contemporaneously) with shocks to other rates is attributed to the FF equation. Although the ordering chosen in this type of analysis is sometimes justified on theoretical grounds, it is very often the case that there exist competing theories that call for different orderings. This problem is not critical here; there exists no particular theory that conflicts with the logic of our proposed ordering (FF, 6MTB, 6MCD, MMDA, SN).

Variance decompositions, given in Table 4, split the k-step-ahead prediction error variance of each rate into the parts (percentages) attributed to innovations in each of the variables in the system. Consider first the wholesale rates. Particularly at short horizons, nearly all FF forecast error variance is due to innovations in itself. At longer forecast horizons, however, 6MTB explains some—up to about 15%—of the FF forecast error variance. Similarly, the prediction error variance for 6MTB at short horizons is attributed mostly to innovations in itself. At longer horizons, however, own-innovations become progressively less important; eventually, FF and MMDA innovations explain most—about 50% and 15%, respectively—of the variance of 6MTB forecast errors.

Turning to the decompositions for retail rates, the one-step-ahead forecast error variance in 6MCD is mostly explained by unexpected lagged movements in itself (75%), but most of the prediction error variance at longer horizons is explained by innovations in FF and 6MTB. As the horizon lengthens, it is first 6MTB that explains much of the variance; FF gradually becomes more important, eventually explaining roughly 60% of the variance. A similar pattern characterizes MMDA. Its one- and two-step-ahead forecast variances are primarily explained by its own innovations (76% and 62%) and to some extent by 6MCD innovations (20% and 16%). At longer horizons, most of the variance (about 75%) is attributed to innovations in FF and 6MTB. Similarly, the SN forecast-error variance is mostly attributed to own-innovations and MMDA innovations at short horizons; at longer horizons, it is FF and MMDA innovations that are most important.

4.4 Impulse-Response Functions

An impulse-response function describes the response of the system of interest rates to an unanticipated unit shock in any one of the rates. A unit shock to a rate in the normalized system is interpreted as a one-standard-deviation unanticipated movement in that variable. We focus on the response to shocks in the two wholesale rates, because this is where most variation originates and because this allows us to focus on the questions of most interest to policymakers: How do retail rates respond to unanticipated movements in wholesale rates? What are the dynamic implications of an innovation in the wholesale cost of funds for the spreads between wholesale and retail rates? How do the speeds of adjustment and short-run patterns of adjustment differ among deposit accounts?

Estimation of the system yields an estimate of .59%, or 59 basis points, for a one-standard-deviation unanticipated shock to FF; for 6MTB, the estimate is .17%, or 17 basis points. For each of the retail rates, such a shock is around two or three basis points. (These magnitudes are also the corresponding diagonal entries of the Choleski factor of the innovation covariance matrix.)

In Figures 2–4, we plot the impulse responses of the retail rates to a one-standard-deviation shock to FF, a one-standard-deviation shock to 6MTB, and joint one-standard-deviation shocks to both FF and 6MTB. Responses to an FF shock are shown in Figure 2; they are substantial in absolute terms but are generally small relative to the 59-basis-point shock. Note that 6MTB displays a characteristic hump-shaped impulse-response pattern, as do all three retail rates. Because all estimated roots of the system are stable, the impulse response must approach 0 as the lag length approaches ∞. The decay is slow, however, due to the proximity of the dominant root to unity.

Given the large degree of negative serial correlation evident in FF, the level around which FF initially cycles following the shock, rather than the amplitude of the shock, might be a more appropriate metric for comparing the response amplitudes. (If FF were nonstationary, the natural comparison would be with the "permanent" component of the shock.) The level around which FF cycles, until decay sets in at about the twelfth week, is about .20 (20 basis points above the unconditional mean). The 6MTB response, although smoother than the FF own-response, is of the same amplitude as the FF own-response and peaks at .20 about 12 weeks out. Among retail rates, the maximal response is greatest for 6MCD (.19), somewhat smaller

Table 4. Variance Decompositions: Levels Data

Week	SE	FF	6MTB	6MCD	MMDA	SN
			Federal funds (FF)			
1	.59	100.0	.0	.0	.0	.0
2	.62	95.0	5.0	.2	.3	.0
3	.71	95.0	4.4	.1	.7	.0
4	.74	91.2	7.5	.2	1.1	.0
5	.79	90.0	8.2	.1	1.5	.0
6	.82	88.0	10.3	.1	2.0	.0
7	.86	86.0	11.3	.1	2.5	.0
8	.90	84.1	13.0	.2	3.0	.0
9	.94	82.8	13.4	.2	3.6	.0
10	.97	81.4	14.2	.3	4.1	.0
15	1.13	77.3	15.5	.6	6.4	.2
20	1.23	75.3	15.2	.9	8.3	.4
			Six-month treasury bills (6MTB)			
1	.19	12.0	88.4	.0	.0	.0
2	.25	12.0	85.3	.1	3.0	.0
3	.32	23.3	71.5	.3	5.0	.0
4	.39	28.3	64.3	.4	7.0	.1
5	.46	35.0	56.1	.5	8.4	.1
6	.52	39.0	50.6	.7	10.0	.2
7	.58	43.0	46.0	.8	11.0	.2
8	.64	45.4	42.0	.9	11.4	.3
9	.70	48.0	39.0	1.0	12.1	.4
10	.75	50.0	36.1	1.0	12.7	.5
15	.95	54.6	28.0	1.3	15.2	.9
20	1.08	56.5	23.8	1.4	16.9	1.4
			Six-month CD's (6MCD)			
1	.04	5.0	21.0	74.4	.0	.0
2	.08	9.0	43.3	48.0	.1	.0
3	.12	18.0	51.0	31.0	1.0	.1
4	.16	26.2	52.4	20.0	2.0	.1
5	.21	33.3	51.0	13.0	3.1	.0
6	.26	39.0	48.4	8.5	4.4	.0
7	.32	43.0	46.0	6.0	6.0	.2
8	.37	46.3	43.0	4.3	7.0	.0
9	.42	50.0	40.2	3.3	8.0	.0
10	.47	51.0	38.0	3.0	8.4	.1
15	.71	57.0	30.0	1.7	11.5	.3
20	.88	59.3	25.0	1.7	14.0	.6
			Money market deposit accounts (MMDA)			
1	.02	1.3	3.0	20.0	76.1	.4
2	.04	10.0	11.2	16.4	62.2	.6
3	.07	19.4	16.5	12.2	51.5	.6
4	.09	28.4	20.0	9.0	43.0	.7
5	.12	35.3	21.5	6.0	37.0	.7
6	.16	41.0	22.4	4.1	32.1	1.0
7	.19	45.0	23.0	3.0	29.0	1.0
8	.22	48.0	23.0	2.1	27.0	1.0
9	.26	51.0	23.0	2.0	25.0	1.0
10	.30	52.0	22.3	2.0	24.0	1.0
15	.47	57.1	20.1	.7	21.1	1.0
20	.61	59.1	17.9	.7	21.0	1.4
			Super NOW's (SN)			
1	.02	1.7	.3	5.2	14.0	79.3
2	.04	3.1	.8	8.0	21.5	66.6
3	.05	7.1	2.8	8.3	26.1	55.7
4	.06	12.2	5.2	7.2	29.1	46.3
5	.07	18.2	7.3	6.0	31.0	38.1
6	.09	24.0	9.0	4.3	31.3	32.0
7	.10	29.0	10.0	3.3	32.0	26.4
8	.12	33.1	11.0	2.5	31.3	22.4
9	.13	36.6	11.2	2.0	31.0	19.3
10	.15	40.0	11.4	2.0	31.0	17.0
15	.23	48.3	11.3	.8	29.1	10.5
20	.30	52.1	11.0	.7	28.5	8.2

NOTE: Each section heading refers to the variable whose forecast variance is analyzed. The first column gives the number of weeks (steps) ahead a forecast is made, plus the standard error of the forecast. Each of the other columns gives the percentage of that variation explained by innovations of the variable heading that column. SE indicates standard errors.

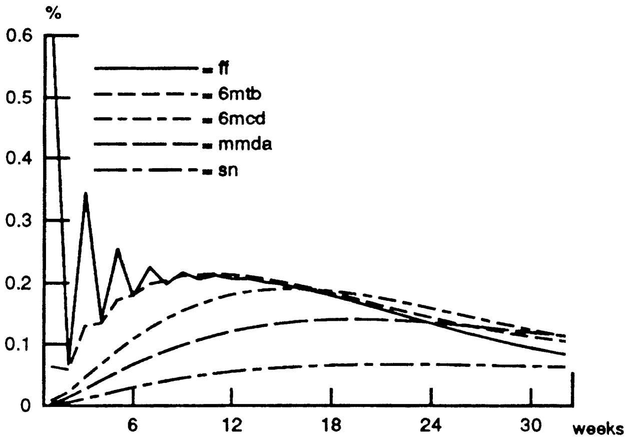

Figure 2. Impulse Responses to (.59) Shock in FF.

for MMDA (.14), and smallest for SN (.07). An identical pattern emerges with respect to the speed of response as indicated by the lag at which maximal response occurs—week 16, 19, and 22 for 6MCD, MMDA, and SN, respectively.

Responses to a one-standard-deviation 6MTB innovation are shown in Figure 3. The qualitative ranking of response patterns among retail rates is similar to that following an FF shock; 6MCD responds the most and SN the least. Although the absolute magnitudes of retail rate responses are smaller than for the FF shock, relative to the size of the initial 17-basis-point 6MTB shock, they are comparable. All have the characteristic hump-shaped pattern. Their response speeds, although still quite slow, are faster than in the case of FF shocks; the maximal responses of .12, .07, and .03 to the 6MTB shock occur at lags of 10, 15, and 16 weeks for 6MCD, MMDA, and SN, respectively.

Finally, we consider the effects of simultaneous shocks to both FF and 6MTB, which may be a better approximation to an unanticipated change in the general opportunity cost of funds. The results appear in Figure 4. As expected, the retail rate response is greater than for the FF or 6MTB shock alone. (The response to the joint shock is the sum of the responses to the

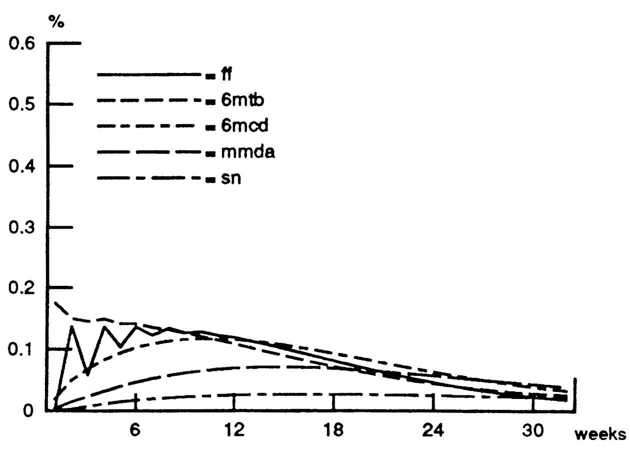

Figure 3. Impulse Responses to (.19) Shock in 6MTB.

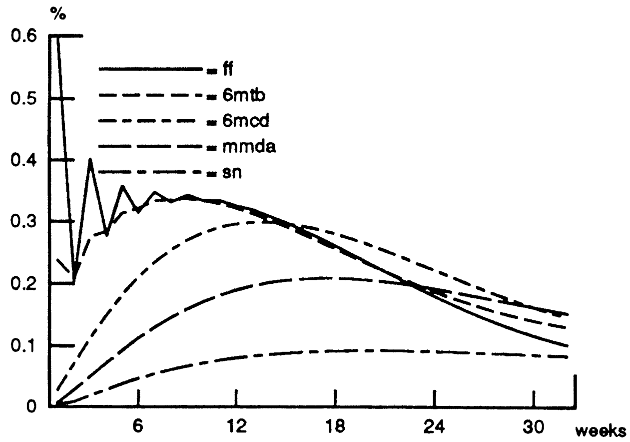

Figure 4. Impulse Responses to FF and 6MTB Shocks.

individual shocks.) The qualitative response pattern is otherwise similar to that of a pure FF or 6MTB shock.

5. UNIT ROOTS AND COINTEGRATION

As discussed earlier, analysis of the levels system is appropriate for studying the multivariate dynamics of interest rates as measured by the impulse responses and variance decompositions, regardless of whether the rates are stationary, integrated, or cointegrated. This is because least squares estimates remain consistent and typically converge at accelerated rates in the presence of unit roots and cointegrating relationships (Sims et al. 1988).

The point estimates of the moduli of the dominant eigenvalues of all the systems analyzed thus far—bivariate and five-variate—are inside the unit circle. Using a battery of unit-root tests, however, we are unable to reject the unit-root null hypothesis for each of our five rates. Augmented Dickey–Fuller (e.g., Fuller 1976) t-type and F-type tests are reported in Table 5. The first of the t-type test statistics reported, $S1$, allows for a nonzero mean under the alternative, whereas the second, $S2$, allows for a linear trend. Both tests make use of five augmentation lags; they may be viewed as an approximation to ARMA representations and are valid in the presence of autoregressive conditional heteroscedasticity. All values of $S1$ and $S2$ are well below their critical points, even at the 20% significance level. Similar results are obtained with the joint F-type tests (Dickey and Fuller 1981) $J1$, $J2$, and $J3$.

It may be of some interest, then, to entertain the possibility that our interest rate data may be integrated or cointegrated and to explicitly impose such restrictions. In this section, we briefly sketch the results of such an analysis and compare them to the results of our earlier levels analysis. Specifically, we redo the bivariate causality analysis in first differences, and then we examine the impulse-response functions associated with the differenced system. Finally, we examine the impulse responses when a particular cointegrating relationship is imposed.

Table 5. Tests for Unit Roots in Retail and Wholesale Rates

Dickey–Fuller test statistic	Interest rate				
	SN	*MMDA*	*6MCD*	*6MTB*	*FF*
Scalar tests					
*S*1: Intercept only	−.34	−.82	−1.17	−1.05	−1.10
*S*2: Intercept and trend	−2.34	−2.34	−2.57	−2.45	−1.88
Joint tests					
*J*1: Intercept only	.64	.52	.72	.79	.66
*J*2: Intercept and trend	2.52	2.20	2.50	2.29	1.26
*J*3: Intercept and trend	3.16	2.97	3.63	3.25	1.83

NOTE: *S*1 is the *t*-type statistic on r_{t-1} in the regression of Δr_t on an intercept, r_{t-1}, $\Delta r_{t-1}, \ldots, \Delta r_{t-5}$, and *S*2 is the *t*-type statistic on r_{t-1} when a linear trend term is included as well. *J*1 is the *F*-type statistic for the null that the coefficients on the intercept and on r_{t-1} are jointly 0 when only an intercept is included. *J*2 is the *F*-type statistic for the null that the coefficients on the intercept, trend term, and r_{t-1} are jointly 0 in the regression containing both intercept and trend. *J*3 is the *F*-type statistic for the null hypothesis that the coefficients on the trend term and r_{t-1} are jointly 0 in the regression containing both intercept and trend.

5.1 Five Unit Roots

Failure to reject the unit root null hypothesis does not, of course, mean that the data have unit roots. Unit-root tests may have poor power, particularly against nearby—and economically reasonable—alternatives (see DeJong, Nankervis, Savin, and Whiteman 1988; Diebold and Rudebusch 1990). If, however, the data are integrated, then Gaussian asymptotic distribution theory is applicable to causality regressions on differenced, but generally not on levels, data. Thus causal analysis of differenced data may provide a useful check on our earlier results. The results of such bivariate causality tests for differenced data are contained in Table 6. The findings parallel our earlier results for levels data; the view that wholesale rates are causally prior to the retail rates is strongly confirmed. Moreover, there appears to be little feedback from retail to wholesale rates; one notable exception, as in the levels version, is the apparent linkage from MMDA to 6MTB.

If the interest rates truly have distinct unit roots, then efficiency of parameter estimates, and hence impulse-response estimates, may be increased by imposing the unit-root restrictions. This is achieved by estimating the system in differences. Then, to obtain the effects of unanticipated wholesale rate changes on the levels of interest rates, we must sum the corresponding weekly changes. Such cumulative impulse-response functions are displayed in Figures 5–7, which show the total response of rates at time $t + k$ to a one-standard-deviation shock at time t. These figures show the permanent effects of wholesale rate innovations on wholesale and retail rates—a characteristic due entirely to the unit-root assumption—as well as the dynamics of the inter-rate spreads.

Consider first the responses to the FF shock, shown in Figure 5. The negative serial correlation in FF is again apparent. In part, the high volatility and negative correlation are the result of institutional factors; Wednesdays are the closing days of the two-week accounting period over which banks must maintain their required average reserve levels. (When Monday data for FF is used instead, the volatility and negative serial correlation are somewhat reduced, though the qualitative characteristics of the system remain unchanged.) The permanent, or long-run, movement in FF is about .40, or two-thirds the initial shock. The estimated long-run responses of retail rates are small, ranging from .08 for 6MCD to .05 for MMDA and .02 for SN. In percentage terms, the long-run responses of retail rates are, therefore, 25% (6MCD), 17% (MMDA), and 7% (SN) of the estimated long-run movement of FF.

The cumulative effects of a 6MTB shock are shown in Figure 6. In the long run, 6MTB rises by more than the original shock (from .19 to .35) due to positive serial

Table 6. Bivariate Interest Rate Causal Patterns, Differenced Data, Five Lags

Δr_i	Δr_j				
	SN	MMDA	6MCD	6MTB	FF
SN	—	.19	.00	.56	.20
MMDA	.02	—	.02	.01	.60
6MCD	.05	.01	—	.39	.49
6MTB	.07	.00	.00	—	.13
FF	.22	.00	.00	.00	—

NOTE: Entries are *p* values for the null hypothesis that Δr_i does not cause Δr_j, using five lags of Δr_i and Δr_j. Intergroup blocks are underlined.

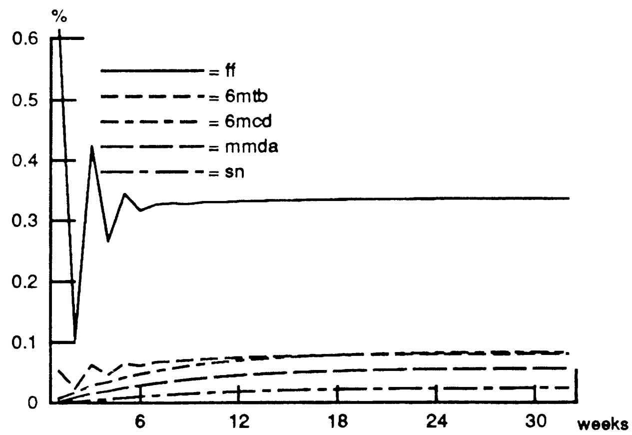

Figure 5. Impulse Responses to (.61) Shock in FF (differenced system).

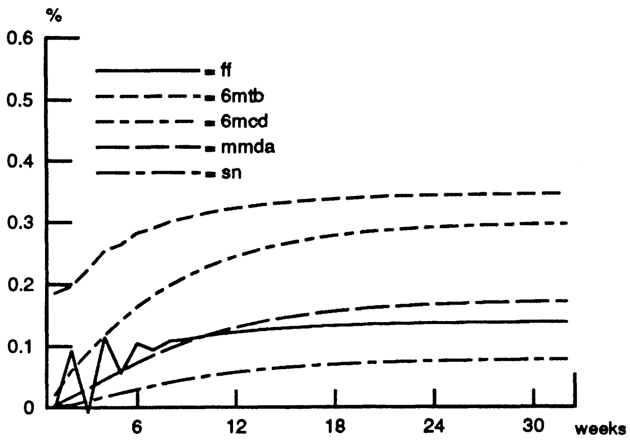

Figure 6. Impulse Responses to (.19) Shock in 6MTB (differenced system).

correlation in the first differences. Retail rates are much more responsive to 6MTB shocks than to FF shocks. In the long run, their responses to the 6MTB shock are .30 (6MCD), .17 (MMDA), and .08 (SN). Their respective long-run responses are, therefore, 87%, 49%, and 23% of the long-run movement in 6MTB.

To examine adjustment speeds, we compute first-quartile, median, and third-quartile lags, shown in Table 7, for each of the wholesale rate shocks. The first quartile lag gives the number of weeks required for 25% of total long-run adjustment, and so forth. For 6MCD, adjustment speeds to FF and 6MTB shocks are identical. In both cases, 25% of 6MCD adjustment occurs in two weeks; the median lag is five weeks, and nine weeks are required for 75% adjustment. In general, MMDA and SN responses are somewhat slower, particularly for shocks to 6MTB.

Although the long-run behavior of the levels and the differenced systems are not comparable, some interesting comparisons of the interim dynamics emerge. In both cases, the relative response magnitudes of retail rates are identical; 6MCD responds the most, SN the least, with MMDA intermediate. On the other hand,

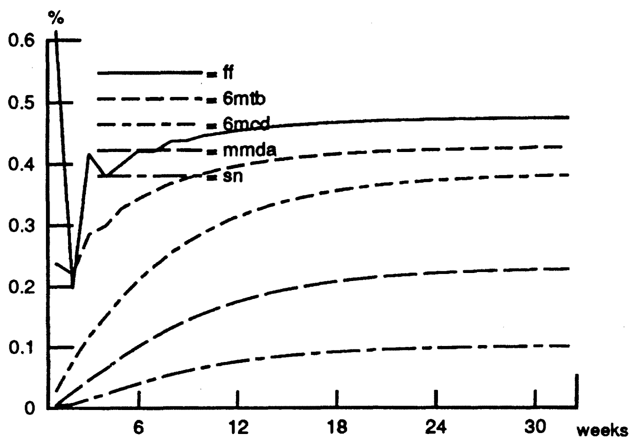

Figure 7. Impulse Responses to FF and 6MTB Shocks (differenced system).

Table 7. Number of Weeks Required for 25%, 50%, and 75% Adjustment

Retail rate	Wholesale rate innovation to		
	FF	6MTB	FF and 6MTB
6MCD	2, 5, 9	2, 5, 9	2, 5, 9
MMDA	2, 5, 9	3, 7, 11	3, 8, 11
SN	2, 6, 11	4, 7, 12	4, 8, 12

NOTE: Each entry is a 3-tuple. The first element gives the number of weeks (rounded up to the nearest integer), required for 25% of the long-run consumer rate adjustment to occur; the second element is the number of weeks required for 50% adjustment; the third element is the number of weeks required for 75% adjustment.

the two analyses yield different conclusions about the relative importance of the innovation sources. In the levels system, most of the retail rate movements are identified with FF rather than 6MTB innovations. In the differenced system, the converse is true. This pattern is also reflected in the variance decompositions. Much of the retail rate forecast error variance at longer lags in the differenced system is explained by 6MTB innovations rather than FF innovations.

Finally, the response of retail rates to simultaneous one-standard-deviation shocks in the two wholesale rates yields results similar to the levels analysis. As can be seen by comparing Figures 4 and 7, the estimated maximal responses of each retail rate to the combined shock in the two systems are quite close.

5.2 Fewer Than Five Unit Roots

Finally, we entertain the possibility that, even if all of the interest rates are integrated, there may be fewer than five unit roots underlying the system; that is, the interest rates may be cointegrated. In particular, we shall consider the possibility of only one underlying unit root and hence four cointegrating relationships. This is designed to capture one fundamental underlying "interest rate" to which the other rates are (stochastically) pegged.

Such a system may be written either in error-correction form (Engle and Granger 1987) or in VAR form (Campbell and Shiller 1987). The VAR form, which is more convenient for our purposes, is composed in the present context of the first difference of one of the variables and the remaining four cointegrating relationships. In particular, it may be reasonable to allocate the unit root to FF, and to postulate that the four cointegrating relationships are simply spreads relative to FF. We shall therefore estimate a two-lag VAR for (ΔFF, 6MTB–FF, 6MCD–FF, MMDA–FF, SN–FF)′.

To be as consistent as possible with the previous analysis, we adopt an analogous ordering. We make ΔFF_t the dependent variable of Equation (1), $6MTB_t - FF_t$ the dependent variable for Equation (2), $6MCD_t - FF_t$ the dependent variable for Equation (3), and so on. Although the impulse-response functions are estimated in terms of changes and spreads, the dynamic behavior of levels can be inferred by first computing the cumu-

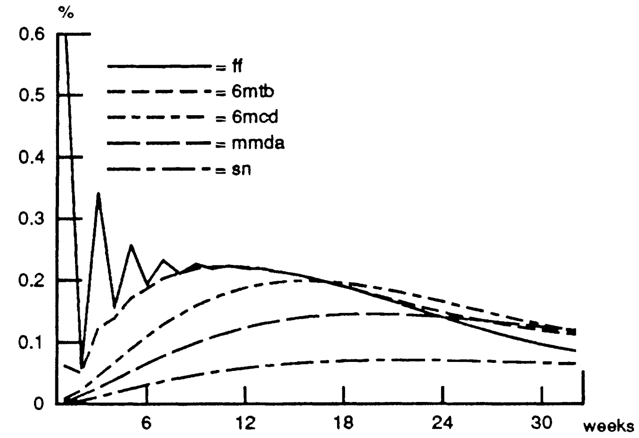

Figure 8. Impulse Responses to (.60) Shock in FF (cointegrated system).

lative impulse response of FF and then unwinding the spreads.

In Figures 8–10, we plot the implied impulse responses of each rate to a one-standard-deviation (.60) innovation in ΔFF, a one-standard-deviation (.17) innovation in the 6MTB–FF spread, and simultaneous innovations in both. The implied responses for both the wholesale and retail rates are close, both in magnitude and shape, to those found in the analysis of levels (Figs. 2–4), which lends support to the hypothesis that the data may be cointegrated in the fashion adopted.

6. SUMMARY AND CONCLUSIONS

We have explored the dynamic relationships among wholesale and retail interest rates, with particular attention given to causality patterns and response patterns of retail rates to unanticipated movements in wholesale rates. We purposefully impose very few restrictions on the model; in light of our desire to ascertain descriptive characteristics of historical behavior, we let the data speak for itself.

Our primary findings may be briefly stated as follows:

1. There is strong evidence of causality from wholesale to retail rates. There is little feedback from retail to wholesale rates, but substantial intra-group feedback.

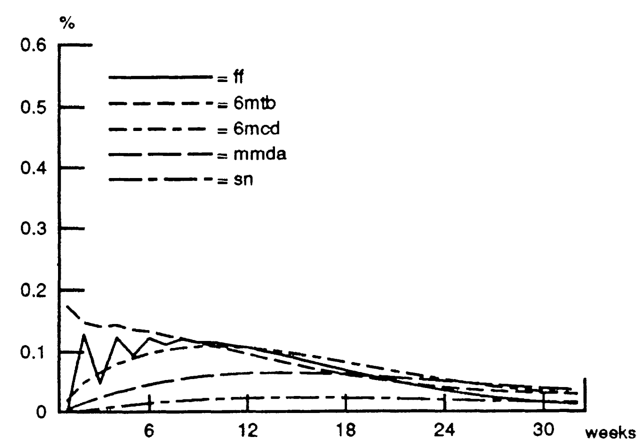

Figure 9. Impulse Responses to (.17) Shock in 6MTB-FF (cointegrated system).

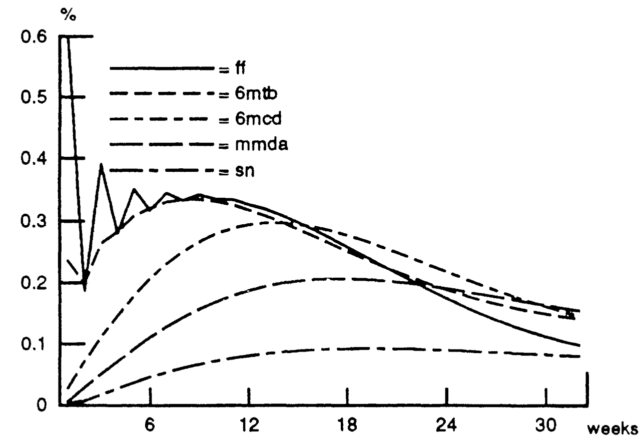

Figure 10. Impulse Responses to FF and 6MTB-FF Shocks (cointegrated system).

2. The dynamics are characterized by dominant roots near, but not necessarily equal to, unity. This induces a substantial amount of shock persistence over horizons of economic interest. A low-ordered time series representation [VAR(2)] provides an adequate approximation.

3. Retail rate behavior in response to an unanticipated shock to the opportunity cost of funds is uniform with respect to the shape of qualitative adjustment patterns. Week-to-week adjustments display a characteristic hump shape.

4. For all retail rates, maximal adjustment takes substantial time, with 6MCD moving the most, followed by MMDA and SN. Speed-of-adjustment rankings match those of adjustment size.

5. Our conclusions regarding causal patterns are unchanged when the data are analyzed in differences rather than in levels. Similarly, impulse-response functions for differenced data are qualitatively similar to those of the levels data, albeit with two exceptions. First, there is a sizeable permanent component associated with the unit root; in fact, the cumulative impulse-response functions estimated with differenced data are monotonically increasing to their long-run value. Second, the importance allocated to FF and 6MTB innovations in terms of their effect on retail deposit rates differs from that obtained in levels regressions.

6. Impulse-response functions for a very simple cointegrated representation are close to those of the levels analysis.

Our findings may have implications for the conduct of monetary policy. Because of the marked sluggishness of deposit rates such as MMDA and SN, movements in wholesale rates will continue to have a strong effect on money demand under retail rate deregulation. Our rankings of adjustment sizes and speeds suggest that a broader aggregate such as M2 may be a somewhat more useful indicator, and possibly more manipulable, than a narrower aggregate. Specifically, we have verified that the greatest intertemporal variation in opportunity costs (greatest degree of price sluggishness) occurs in the more liquid or "money-like" components. If most of the portfolio shifts resulting from these changes in opportunity cost are movements of assets to or from other slightly less liquid components of M2 that follow wholesale rates more closely (such as CD's), then M2 ought to remain more insulated than narrower aggregates from the dynamic opportunity cost effects of changing interest rates.

Our findings also indicate a number of promising directions for future research. In particular, the results indicate that a deeper analysis of cointegrating relationships (formal testing procedures, as well as estimation rather than imposition of cointegrating vectors, etc.) may prove fruitful. The recent maximum-likelihood testing and estimation procedures of Johansen (1988) may prove particularly valuable in this regard. Finally, use of generalized long-memory approximations to the Wold representations of wholesale and retail interest rates such as those obtained via fractional integration and fractional cointegration (see Diebold and Rudebusch 1989, in press; Sowell 1986) may prove equally valuable.

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