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11 Forecasting Bank Portfolios

Robert Jacobson

11.1 Introduction

The risks in a bank can be divided into wealth effects and operating or income effects. Chapters 9 and 10 analyzed possible changes in value as a result of unanticipated movements in interest rates, risk premiums, and loan losses, and from aggregate net income. These risks and probabilities depend upon the portfolio of assets and liabilities in the bank at its initial examination.

A bank, however, is a dynamic organization. Changes will occur between examinations. Both the policies of the bank and the impact of macroevents will cause shifts. The economy and individual banks wax and wane. If interest rates rise, cash flows may alter because of disintermediation or increased loan takedowns. The rates that apply to new or renewed loans or liabilities will differ from initial ones. This may lead to losses or to increased profitability. Some loans such as mortgages may be extended beyond their initial expectations, or they may be paid off more rapidly than seemed likely.

Projections of the bank's portfolio aid in risk measurement for several reasons:

1. The risk of insolvency depends directly on the expected capital/asset ratio. Therefore, estimates are needed for the expected increase or decrease in both capital and assets.
2. Risk depends upon the share of each activity in the total portfolio. We would like estimates of portfolio movements.
3. The risk of high transaction or liquidation costs depends upon the likelihood of major outflows of liabilities.

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4. In obtaining present values of future flows as analyzed in chapters 3, 13, and 14, the value of an asset can shift either because discount rates move or because the time frame of expected flows after the end of the period alters. Therefore these measures should be based not only on cash flows expected initially, but also on whatever expectations alter during the period.

In this chapter time-series analysis is used to forecast various bank assets and liabilities. Although the analysis was used only for short-term forecasting of selected portfolio items, the techniques and results presented can be extended for other necessary purposes such as prediction of the capital/asset ratio. The analysis, which appears to forecast bank portfolios well, indicates that macroeconomic variables are extremely unimportant compared with the portfolio item's past values in determining the forecast.

11.2 Macromodeling

Theories of why portfolios alter are detailed in numerous economic and financial studies. Portfolios are thought to be sensitive to a variety of macro variables. Included as potential causes are such factors as the level of long- and short-interest rates; relative rates such as the difference between commercial paper and prime interest rates or between long-term and short-term rates; the amount of money or reserves; macro demand factors such as income, output, or employment; micro factors such as internal funds available to nonfinancial corporations, investment in plant and equipment, inventories, or housing. The relationship between the dependent and independent variables can be lagged and can depend on the rate of stock adjustments. A few extremely complex models have been developed for aggregate movements in bank portfolios, as for example by Hunt (1976), Bosworth and Duesenberry (1975), and Data Resources Incorporated.

11.2.1 Regression Models

With the cooperation of the Federal Reserve Board and the Federal Reserve Bank of San Francisco, we developed a data base of the series of portfolio changes for individual banks. We applied to these data standard regression models of the form:

$$Y_t = B_0 + \sum_{i=1}^{k} B_i X_{it} + \varepsilon_t \,, \tag{1}$$

where X_i consisted of one to ten variables in an equation and there were weekly, monthly, or quarterly observations covering more than ten years.

We tested literally hundreds of different models using the variables of the traditional theory. We concluded that at this time we could not develop an adequate econometric forecasting system for the portfolios of individual banks. One of the major problems is that there is a high probability that error terms are not independent from one period to the next. While we attempted traditional econometric corrections of first differencing and simple autoregressive error processes, they do not seem to be as effective as more complicated error processes.

Second, it seems plausible to expect past values of both the dependent and independent variables to influence current values of the dependent variable. Economic theory says very little about logical patterns of the distributed lags necessary to handle this problem. Finally, the number of specific factors influencing the movements in individual banks is large. These specific factors are likely to be much less important when their effect is averaged over a number of individual banks into large aggregates.

Some fairly adequate models have been built for more aggregated data. Thus chapters 14 and 15 contain models of demand for commercial loans and demand and time deposits. Other fairly satisfactory equations can be found for the aggregate mortgage flows and for consumer loans. However, we encountered great problems in applying these models to the more complex situation of individual institutions.

As a result, we turned to the more tractable approach of time-series analysis. It has been developed by Box and Jenkins (1976), Granger and Newbold (1977), Haugh (1972), and others, and used in bank modeling by Cramer and Miller (1976). The tools are autoregressive moving average (ARMA) and transfer function analysis. ARMA analysis allows for the modeling of a series based solely on past values of that series. By using autoregressive and moving average terms, the series can be parsimoniously modeled. Transfer function analysis uses univariate techniques but allows for the inclusion of other series. This analysis is similar to standard econometrics in that it relates one group of variables to another variable. It differs from standard econometrics in that the structure of the model is determined entirely by the data. The analysis allows for the identification, estimation, and checking of a wide variety of distributed lag and error structures. Economic theory is used to suggest possible relevant variables and "plausible" specifications.

11.3 Transfer Models

The transfer function model is

$$Y_t = C + V(B)X_t + \psi(B)\eta_t\,, \tag{2}$$

where C is a constant, η_t is the error term, $V(B) = (v_0 + v_1B + v_2B^2 + v_3B^3 \ldots)$, the transfer function (a polynomial in B, the backward shift operator such that $B^kX_t = X_{t-k}$). The transfer function is relating input (exogenous) variables to the output (endogenous) series. The v_k are called impulse response weights and indicate how the input series X_t is transferred to the output series Y_t. The obvious problem in estimating (2) is that it requires an infinite series. To overcome this problem it is necessary to approximate the transfer function by the ratio of two lower-order polynomials. The same is true for $\psi(B)$, so that (2) can be rewritten as:

$$Y_t = C + \frac{\omega(B)}{\delta(B)} X_{t-L} + \frac{\theta(B)}{\phi(B)} \eta_t, \tag{3}$$

where $\omega(B)$, $\delta(B)$, $\theta(B)$, ϕB are polynomials in B of degree s, r, q, and p, respectively and L is the lag time before any effects are felt.

The first step in the estimation is to make a crude guess at $V(B)$. This is done on the basis of cross-correlation analysis. The cross-correlations between two series are usually hard to interpret because of autocorrelation. However, by transforming the exogenous (input) series to white noise, the cross-correlation function becomes easier to interpret. With the input series white noise, and under the assumption that the two series are not cross-correlated, the cross-correlations will be asymptotically distributed $N(0, 1/N)$.

Starting with $Y_t = V(B)X_t + \psi(B)\eta_t$ (assume Y and X are stationary with zero mean), the exogenous series is modeled via autoregressive and moving average parameters to transform it to white noise (i.e., $\varepsilon_t = \theta(B)\phi(B)^{-1}X_t$). Multiplying through, prewhitening, by $\theta(B)\phi(B)^{-1}$ and letting $Z_t = \theta(B)\phi(B)^{-1}Y_t$ yields:

$$Z_t = V(B)\varepsilon_t + \theta(B)\phi(B)^{-1}\psi(B)\eta_t. \tag{4}$$

Since by definition ε_t and η_t are uncorrelated, multiplying (4) by ε_{t-k} and taking expectations gives

$$E(Z_t, \varepsilon_{t-k}) = V_t \operatorname{var}(\varepsilon_t), \text{ or}$$

$$V_k = \operatorname{cor}(Z_t, \varepsilon_{t-k}) \left[\frac{\operatorname{var}(Z_t)}{\operatorname{var}(\varepsilon_t)}\right]^{1/2}.$$

In other words, the V_ks can be tentatively identified because they are constant multiples of the cross-correlations between Z_k and ε_{t-k}.

Thus the transfer function modeling procedure is:

1. Transform the data via differencing, logs, and so forth to produce stationary time series Y and X.
2. Build a univariate model for X_t, the exogenous series, to obtain white-noise residuals (ε_t).
3. Transform the output series, the bank variables, by the same parameters used in the univariate modeling of X, the macro variable, to obtain $\hat{Z}_t$.

4. Calculate the correlation between $\hat{Z}_t$ and $\hat{\varepsilon}_{t-k}$ and obtain an estimate of the transfer function ($\hat{V}(B)$).
5. Use the estimate of $\hat{V}(B)$ to suggest the appropriate order of the polynomials $\hat{\omega}(B)$ and $\hat{\delta}(B)$. The V_k will have a certain grouping, based on the true values of (r, s, L). The size and pattern of the groupings will provide identification clues.
6. Identify the error structure polynomials $\theta(B)$, $\phi(B)$ by using the standard univariate modeling technique on the series $U_t = Y_t - \hat{\omega}(B)\hat{\delta}(B)^{-1}X_{t-L}$.

11.3.1 Diagnostic Check

Once a model is tentatively identified, numerous diagnostic checks can be employed to test for adequacy and possible changes. First, since the residuals should be white noise, autocorrelations of the residuals should be compared with $2/\sqrt{N}$, and Q (the Box-Pierce statistic) $= N \sum_{j=1}^{k} \hat{p}_j^2(\hat{\alpha})$ should be distributed $\chi^2(k-p-q)$ under the null hypothesis of no correlations between the residuals and the prewhitened input series should be distributed $N(O, 1/N)$. Last, t-statistics can be checked and parameters can be dropped or added to see if the model can be improved. The model can then be reestimated and diagnostic checks can be employed on the new model.

11.3.2 Multiple Inputs

The transfer function model in (2) and (3) can easily be extended to include multiple inputs by putting a summation sign in front of the X_t to give:

$$Y_t = C + \sum_{i=1}^{k} V_i(B)X_{it} + \psi(B)\eta_t \tag{3'}$$

$$Y_t = C + \sum_{i=1}^{k} \omega_i(B)\delta_i(B)^{-1}X_{it-L_i} + \theta(B)\phi(B)^{-1}\eta_t. \tag{4'}$$

But modeling a multiple input transfer function is considerably more difficult than modeling the single input case owing to correlation between the exogenous variables. Because of this, most transfer function analysis has been concerned with only one input.

Excluding relevant variables, however, will lead to biased coefficients. From the standpoint of forecasting, this may not be as major a problem as it seems. The model would then be testing to see if the use of the exogenous series and past values of the output series lead to better forecasts than just use of past values of the endogenous series.

Furthermore, if additional variables were tested to see if they too were relevant, then the model could be expected to give better forecasts and would have more credibility. One easy way of using multiple variables is a stepwise regression procedure. However, just as in OLSQ, as long as the independent variables are not orthogonal, the estimated parameters will be biased and the order in which they are included in the model will be important. So, to have adequate confidence in the models' forecasts, it seems necessary to suffer through the difficulties of modeling the multiple inputs simultaneously. Therefore in our models, though we have in no way tested for the inclusion of all relevant variables, we have tested for the possible inclusion of a number of macro variables that we felt would be most important.

11.3.3 Feedback

The other major issue to be addressed is the notion of feedback and causality. It may be that series X influences series Y and series Y influences series X so that the transfer function procedure outlined would not be correct. Although there are numerous methods of testing for causality (Hsiao 1977), we will not report the results, for two reasons. (In fact, using two standard feedback tests [Sims 1972; Granger 1969] on a very few occasions feedback might be concluded.) First, since our left-hand side variables are small groups of banks and our inputs are macro variables, theory tells us it is doubtful that these banks can significantly influence the economy variables. Next, trying to build a complete transfer function for the banking sector or even trying to model a bank simultaneously is beyond the scope of this study. A vector ARMAX model (Hillmer and Tiao 1977) of the necessary size is really not feasible at this time. In general, however, we felt that the single input transfer function model would give adequate forecasts.

11.4 Fitting the Model

11.4.1 The Variables Defined

The methodology outlined in the preceding section was used to model 9 bank variables (see Appendix). From the twenty-two bank groups, we selected three for modeling. The banks were selected to be representative of the reporting banks and extremes for the classifications used in aggregating. Thus, group 1 banks had assets over $1 billion, a ratio of time and savings deposits to assets under 20 percent, and a ratio of total deposits to loans under 1.2. There were twenty-one banks that were averaged in this group. Group 2 banks had assets between $0.5 billion and $1 billion, a ratio of time and savings deposits to assets over 35 percent, and a deposit-to-loan ratio between 1.2 and 1.5. Twenty-three banks fell into this grouping. Group 3 banks were under $0.5 billion in size, had a ratio of time and savings deposits to assets over 35 percent and a deposit-to-loan ratio over 1.5. This group included fifty-five banks.

The bank variables were:

1	GOVS	United States Treasury Securities + Securities of Other Government Agencies and Corporations
2	OSEC	Other Securities + Federal Funds Sold
3	MUNI	Obligations of State and Political Subdivisions
4	CIL	Commercial and Industrial Loans + Farm Loans + Loans to Carry Securities + Loans to Financial Institutions + Other Loans
5	ESTATE	Real Estate Loans
6	CONSUMER	Installment Loans
7	DD	Demand Deposits − Cash Assets
8	TD	Time and Savings Deposits − Large Certificates of Deposit
9	PM	Federal Funds Purchased + Other Purchased Money + Large Certificates of Deposit

The macroeconomic variables modeled as potential inputs were:

1	TBILL	Three-Month Treasury Bill Rate
2	UNEMP	Unemployment Rate (Seasonally Adjusted)
3	PI	Personal Income (Seasonally Adjusted)
4	MONBASE	Monetary Base (Seasonally Adjusted)
5	CPPR	Commercial Paper Rate/Prime Interest Rate
6	HSFR	Housing Starts: New Private Housing Units (Seasonally Adjusted)
7	IVMT	Manufacturing and Trade Inventories (Seasonally Adjusted)
8	MU	Manufacturing Unfilled Orders (Seasonally Adjusted)

TBILL, UNEMP, PI, and MONBASE were tested as possible inputs for all bank variables. HSFR was included only in the Real Estate Loan model, and MU, IVMT, and CPPR were exogenous factors for the loan grouping entitled CIL.

The time period used for identification, estimation, and diagnostic checking was from July 1968 to September 1975 (eighty-seven observations). The remaining twelve observations were withheld to check the forecasting ability of the model.

11.4.2 The Fitting

The first step in the procedure was to get each series stationary. For the macro variables, taking logs and first differences appeared to yield stationarity for all variables except MU and IVMT, which required second differencing. For the bank variables, all required taking logs and first differencing. However, some variables (GOVS, MUNI, DD) had a twelve-month seasonal component that, because the autocorrelations at lags of multiples of twelve were large and died out very slowly, suggested the need of taking twelve-month differences in addition to the first differences.

It must be pointed out that no attempt was made in any part of the univariate or transfer function modeling process to make the models similar between variables in a single bank or between a single variable in the different bank groups. However, on the few occasions in the transfer function modeling when parameters appeared to have "wrong signs at unusual locations" we decided to view the correlations as sampling error and not try to model it.

11.5 Results

For the sake of space, and because the models were not greatly different for the different bank groupings, only the results for bank group 2 will be presented in detail. This group was chosen for more detailed discussion, since it was modeled more carefully and its behavior appeared to be most typical. The univariate models for bank group 2 are reported in table 11.1. The parameter structures are very simple, yet they do not suggest model inadequacy based upon the Box-Pierce statistics. In general, the models contain an autoregressive, usually first-order, parameter and moving average terms, which are factors of twelve, to model the seasonal factors. The ARMA models are quite similar for the different items. The models for bank groups 1 and 3 also showed this similarity across portfolio items. In addition, as noted earlier, the models for the different bank groups are not much different. An earlier indication that the groupings would be similar was that to obtain stationarity GOVS, MUNI, and DD had to have a twelve-month differencing for all three groups. The various models have much the same parameter structure, and the magnitudes of the coefficients are close. However, the differences are significant enough for both the bank variables and for the bank groupings to warrant greater disaggregation in future study.

The univariate models, prewhitening transformations, for the macro variables are in table 11.2. The transfer function models are presented in table 11.3. The exogenous and endogenous variables in the transfer functions are the original variables after being logged and differenced to achieve stationary series. One can quickly see that the inputs do not have too great an effect, because the transfer function error term structure and coefficients are almost exactly the same as that of the univariate models. Some facts are immediately obvious from these transfer function models. First, various macro variables that were hypothesized to have an effect on bank variables had no influence at all. For instance, the monetary base and personal income were never significant. In addition, not only were most macro variables insignificant, but they also had coefficients that

Table 11.1 **Univariate Models for Bank Group 2**

Variables	Models	Residual Standard Error	Box-Pierce Statistics of Model Adequacy: Q	Box-Pierce Statistics of Model Adequacy: Degrees of Freedom
GOVS	$(1-.50B)\,(1-B)\,(1-B^{12})Z_t = (1+.28B^4-.66B^{12})\varepsilon_t$	.025898	3.86	9
	[4.71] [2.96] [6.41]		7.27	21
			11.28	33
OSEC	$(1-B)Z_t = .0193 + (1+.23B^{12})\varepsilon_t$	.10607	10.95	10
	[1.50] [2.00]		17.67	22
			20.81	34
MUNI	$(1-.42B)\,(1-B)\,(1-B^{12})Z_t = (1-.85B^{12})\varepsilon_t$	.014005	11.12	10
	[3.83] [9.58]		17.31	22
			32.02	34
CIL	$(1-.22B)\,(1-B)Z_t = .0045 + (1+.24B^6+.23B^{12})\varepsilon_t$	.014303	8.14	8
	[2.00] [2.00] [2.00] [2.00]		11.29	20
			19.52	32
ESTATE	$(1-B)Z_t = .0094 + (1+.18B)\varepsilon_t$	.011661	7.59	10
	[6.35] [1.72]		12.00	22
			19.75	34
CONSUMER	$(1-.38B-.21B^2)\,(1-B)Z_t = .0035 + (1+.29B^{12})\varepsilon_t$	.0097055	3.96	8
	[3.42] [1.97] [2.20] [2.56]		14.35	20
			23.56	32

Table 11.1 (continued)

Variables	Models	Residual Standard Error	Box-Pierce Statistics of Model Adequacy	
			Q	Degrees of Freedom
DD	$(1-B)\ (1-B^{12})\, Z_t = (1-.73B^{12})\, \varepsilon_t$	.020258	9.82	11
	[7.64]		16.31	23
			20.71	35
TD	$(1-.15B)\ (1-B)\, Z_t = .0074 + (1+.36B^{12})\, \varepsilon_t$	.01116	8.01	9
	[1.38] [4.63] [2.65]		15.28	21
			21.07	33
PM	$(1-B)\, Z_t + .014 + (1+.34B^3+.25B^{12})\, \varepsilon_t$	.033568	5.01	9
	[3.15] [2.29]		11.26	21
			14.55	33

Note: T-statistics in brackets; Z_t = log of original variable.

Table 11.2 **Univariate Models for Macro Variables**

Variables	Models	Residual Standard Error	Box-Pierce Statistics of Model Adequacy: Q	Degrees of Freedom
TBILL	$(1-.31B)\ (1-B)Z_t = \varepsilon_t$	.04511	11.55	11
	[2.00]		17.13	23
			21.48	35
UNEMP	$(1-B)Z_t = (1+.33B+.20B^2+.27B^4)\varepsilon_t$	.020613	2.43	9
	[3.14] [2.00] [2.70]		12.37	21
			19.58	33
MONBASE	$(1-B)Z_t = .006 + \varepsilon_t$	.003305	10.65	11
	[16.77]		19.32	23
			20.83	35
PI	$(1-B)Z_t = .007 + \varepsilon_t$	.005641	13.96	11
	[11.67]		22.96	23
			39.81	35
HSFR	$(1+.28B)\ (1-B)Z_t = (1+.23B^3-.49B^{12})\varepsilon_t$	.069541	9.19	9
	[2.60] [2.25] [4.37]		21.34	21
			27.19	

Table 11.2 (continued)

Variables	Models	Residual Standard Error	Box-Pierce Statistics of Model Adequacy: Q	Box-Pierce Statistics of Model Adequacy: Degrees of Freedom
CPPR	$(1-.16B+.24B^2)\ (1-B)Z_t = (1-.15B^6+.49B^{12})\varepsilon_t$	.044575	6.27	8
	[1.44] [2.24] [1.45] [4.35]		13.18	20
			20.18	33
IVMT	$(1+.32B)\ (1-B)^2Z_t = \varepsilon_t$	.00350	8.13	11
	[3.22]		15.87	23
			19.91	35
MU	$(1-B)^2Z_t = \varepsilon_t$	.0066619	11.65	12
			29.02	24
			37.33	36

Note: T-statistics in brackets; Z_t = log of original variable.

Table 11.3 **Transfer Function Models for Bank Group 2**

Variables	Models	Residual Standard Error	Box-Pierce Statistics of Model Adequacy: Q	Degrees of Freedom
GOVS	$Y_t = -.0042 - .022\text{TBILL}_{t-2} + \left(\frac{.22}{-.74B}\right)\text{UNEMP}_{t-3} + \frac{(1-.19B^3-.57B^{12})}{(1-.20B)}\varepsilon_t$	.02369	2.9 5.68 9.37	8 20 32
OSEC	$Y_t = .025 - .32\text{UNEMP}_{t-1} + \frac{(1+.23B^{12})}{(1+.19B)}\varepsilon_t$	.10309	7.58 16.84 20.21	9 21 33
MUNI	No significant variables found			
CIL	$Y_t = .0047 + .077\text{CPPR}_t + \frac{(1+.31B^6+.28B^{12})}{(1-.19B)}\varepsilon_t$	.013824	10.93 14.51 23.97	8 20 32
ESTATE	$Y_t = .0094 + .048\text{TBILL}_{t-3} + \varepsilon_t$	.01151	7.42 13.66 19.88	11 23 35

Table 11.3 (continued)

Variables	Models	Residual Standard Error	Box-Pierce Statistics of Model Adequacy: Q	Degrees of Freedom
CONSUMER	$Y_t = .0095 + \frac{.046}{(1-.68B)}\text{TBILL}_t - .075\text{UNEMP}_t + (1+.28B^{12})\varepsilon_t$	.00899	7.25 17.89 28.97	10 22 34
DD	No significant variables found			
TD	$Y_t = .0090 - .046\text{TBILL}_t + (1+.42B^{12})\varepsilon_t$	.010665	11.31 22.82 28.36	10 22 34
PM	No significant variables found			

were of extremely small magnitude. These two factors give added confidence in excluding particular variables from the models.

In addition to those variables with no effect, others that we felt would have the greatest impact also had little or no effect. For instance, the Treasury bill rate, although significant on numerous occasions, was not that influential a driving variable. In addition, it was never a significant factor in modeling demand deposits.

The result of the unimportance of the macroeconomic variables was also apparent in the other two bank groups modeled. Basically, the variables that were found to be significant for bank group 2 were significant for the other bank groupings. However, though the lag structure of the transfer functions were similar, they were definitely different and once again indicate the need for further disaggregation.

Although the major difficulty in transform function analysis usually is determining $\omega(B)$ and $\delta(B)$ from the estimate of $V(B)$, this was not the case in these models. In general, the cross-correlations of the prewhitened inputs and outputs were very small compared with their standard errors. So the identification of $\omega(B)$ and $\delta(B)$ usually consisted of picking out the only significant, or nearly significant, lag and then trying overparameterization to see if the model could be improved. In fact, the additional factors generally did very little to improve the model and were subsequently dropped.

11.6 Forecasts

Because of the very nature of time-series modeling, there is little doubt it will yield good one-period-ahead forecasts. Therefore, a better test of the forecasting ability of the models is to forecast from a fixed origin a number of periods away. Table 11.4 displays the forecasts generated from the univariate and transfer function model for one through twelve periods away for bank group 2. (The inputs for the transfer function were the actual values.) No transfer function forecasts were generated for the models that contained no significant exogenous variables.

With few exceptions, the point forecasts are fairly accurate for the forecasts one through twelve periods ahead. The mean absolute percentage error[1] using the forecast from the transfer function when significant exogenous variables were found, and otherwise using the univariate forecast, for bank group 2 were 0.97 percent and 5.18 percent for the one- and twelve-months-ahead forecasts. The forecast errors for the one- and twelve-months-ahead forecasts for bank group 1 were 0.95 percent and 9.36 percent, and were 0.86 percent and 10.9 percent for bank group 3.

1. Mean absolute percentage error $= \frac{1}{K}\sum_{i=1}^{K} \left| \hat{X}_{t+j,i} - X_{t+j,i} \right| / X_{t+j,i}$, where $\hat{X}_{t+j,i}$ = the jth period ahead forecast of the ith variable, and $X_{t+j,i}$ = the actual value of variable i at period $t+j$.

Table 11.4 **Bank Group 2 Forecasts (in Thousands of Dollars)**

Periods Ahead	Univariate Model Forecasts: 95 Percent Lower Confidence Limit	Point Forecast	95 Percent Upper Confidence Limit	Actual Value	Transfer Function Model Forecasts: 95 Percent Lower Confidence Limit	Point Forecast	95 Percent Upper Confidence Limit
		GOVS				GOVS	
1	0.5068443E+05	0.5330687E+05	0.5606495E+05	53150.	0.5074706E+05	0.5315701E+05	0.5568135E+05
2	0.4916806E+05	0.5385238E+05	0.5898294E+05	57621.	0.4952558E+05	0.5324235E+05	0.5723800E+05
3	0.4940005E+05	0.5608324E+05	0.6367050E+05	58916.	0.5062158E+05	0.5552074E+05	0.6089398E+05
4	0.4919756E+05	0.5764029E+05	0.6753181E+05	58955.	0.5122987E+05	0.5693568E+05	0.6327692E+05
5	0.4744304E+05	0.5760215E+05	0.6993569E+05	58897.	0.5086723E+05	0.5731649E+05	0.6458337E+05
6	0.4752411E+05	0.5972524E+05	0.7505875E+05	57124.	0.5309996E+05	0.6079365E+05	0.6960200E+05
7	0.4733996E+05	0.6142808E+05	0.7970869E+05	61343.	0.5487432E+05	0.6393366E+05	0.7448856E+05
8	0.4491569E+05	0.6002267E+05	0.6021069E+05	63922.	0.5244655E+05	0.6231486E+05	0.7403987E+05
9	0.4382023E+05	0.6016991E+05	0.8261969E+05	63487.	0.5065457E+05	0.6143992E+05	0.7452162E+05
10	0.4361910E+05	0.6142228E+05	0.8649175E+05	60714.	0.4970150E+05	0.6155522E+05	0.7623594E+05
11	0.4324491E+05	0.6234743E+05	0.8988800E+05	59361.	0.4860038E+05	0.6144642E+05	0.7768787E+05
12	0.4282082E+05	0.6312070E+05	0.9304394E+05	59066.	0.4769933E+05	0.6153339E+05	0.7937962E+05
		OSEC				OSEC	
1	0.3161670E+05	0.3892259E+05	0.4791668E+05	41650.	0.3275624E+05	0.4009055E+05	0.4906702E+05
2	0.3017991E+05	0.4049495E+05	0.5433545E+05	46737.	0.3271600E+05	0.4261159E+05	0.5550025E+05
3	0.2877111E+05	0.4124157E+05	0.5911713E+05	51523.	0.3253724E+05	0.4483742E+05	0.6178742E+05
4	0.2740093E+05	0.4152751E+05	0.6293700E+05	53822.	0.3138801E+05	0.4537979E+05	0.6560862E+05
5	0.2670347E+05	0.4250614E+05	0.6766050E+05	53504.	0.3175607E+05	0.4791690E+05	0.7230200E+05
6	0.2608369E+05	0.4340320E+05	0.7222275E+05	57240.	0.3109985E+05	0.4878055E+05	0.7651287E+05
7	0.2462327E+05	0.4267935E+05	0.7397581E+05	53301.	0.2935030E+05	0.4770884E+05	0.7755056E+05
8	0.2402454E+05	0.4325341E+05	0.7787269E+05	52601.	0.2923082E+05	0.4912063E+05	0.8254419E+05
9	0.2415475E+05	0.4506694E+05	0.8408394E+05	48795.	0.2892427E+05	0.5014781E+05	0.8694431E+05

10	0.2323146E+05	0.4483147E+05	0.8651462E+05	49830.	0.2779575E+05	0.4963693E+05	0.8864025E+05
11	0.2251372E+05	0.4486308E+05	0.8939856E+05	50096.	0.2780100E+05	0.5106237E+05	0.9378669E+05
12	0.2149473E+05	0.4416607E+05	0.9074969E+05	49271.	0.2694565E+05	0.5083968E+05	0.9592162E+05
		MUNI				MUNI	
1	0.9044650E+05	0.9296156E+05	0.9554650E+05	92091.			
2	0.8886019E+05	0.9319725E+05	0.9774594E+05	91963.			
3	0.8794119E+05	0.9382319E+05	0.1000986E+06	91750.			
4	0.8801625E+05	0.9528469E+05	0.1031532E+06	91294.			
5	0.8814231E+05	0.9664456E+05	0.1059667E+06	90753.			
6	0.8898794E+05	0.9868481E+05	0.1094382E+06	90592.			
7	0.8847981E+05	0.9913519E+05	0.1110737E+06	90396.			
8	0.8773100E+05	0.9922944E+05	0.1122348E+06	90704.			
9	0.8713481E+05	0.9942469E+05	0.1134478E+06	90270.			
10	0.8660494E+05	0.9963744E+05	0.1146311E+06	88599.			
11	0.8569644E+05	0.9936250E+05	0.1152077E+06	88151.			
12	0.8484094E+05	0.9910062E+05	0.1157569E+06	88551.			
		CIL				CIL	
1	0.1879079E+06	0.1932503E+06	0.1987446E+06	192471.	0.1871061E+06	0.1924029E+06	0.1978495E+06
2	0.1851102E+06	0.1934777E+06	0.2022231E+06	192917.	0.1839391E+06	0.1920681E+06	0.2005562E+06
3	0.1838018E+06	0.1945286E+06	0.2058811E+06	192440.	0.1828061E+06	0.1930989E+06	0.2039711E+06
4	0.1819655E+06	0.1945922E+06	0.2080949E+06	194684.	0.1796285E+06	0.1915604E+06	0.2042846E+06
5	0.1798702E+06	0.1940903E+06	0.2094344E+06	192986.	0.1780580E+06	0.1914741E+06	0.2059009E+06
6	0.1784426E+06	0.1941057E+06	0.2111434E+06	194565.	0.1766626E+06	0.1914009E+06	0.2073686E+06
7	0.1779779E+06	0.1955766E+06	0.2149152E+06	197508.	0.1753881E+06	0.1919932E+06	0.2101703E+06
8	0.1772184E+06	0.1966550E+06	0.2182231E+06	199124.	0.1753973E+06	0.1939166E+06	0.2143909E+06
9	0.1761422E+06	0.1972391E+06	0.2208626E+06	202024.	0.1740861E+06	0.1942351E+06	0.2167159E+06
10	0.1753993E+06	0.1980661E+06	0.2236617E+06	204102.	0.1720844E+06	0.1936331E+06	0.2178801E+06
11	0.1747415E+06	0.1988822E+06	0.2263577E+06	205038.	0.1713676E+06	0.1943552E+06	0.2204262E+06
12	0.1740551E+06	0.1995761E+06	0.2288389E+06	204290.	0.1705629E+06	0.1948847E+06	0.2226744E+06

Table 11.4 (continued)

	Univariate Model Forecasts				Transfer Function Model Forecasts		
Periods Ahead	95 Percent Lower Confidence Limit	Point Forecast	95 Percent Upper Confidence Limit	Actual Value	95 Percent Lower Confidence Limit	Point Forecast	95 Percent Upper Confidence Limit
		ESTATE				ESTATE	
1	0.1356043E+06	0.1367392E+06	0.1419464E+06	138278.	0.1366627E+06	0.1397807E+06	0.1429696E+06
2	0.1351799E+06	0.1400539E+06	0.1451036E+06	139147.	0.1370026E+06	0.1414437E+06	0.1460287E+06
3	0.1352175E+06	0.1413612E+06	0.1478256E+06	141808.	0.1372953E+06	0.1427659E+06	0.1484543E+06
4	0.1354694E+06	0.1427209E+06	0.1503606E+06	142558.	0.1371988E+06	0.1436072E+06	0.1503147E+06
5	0.1358531E+06	0.1440734E+06	0.1527911E+06	143577.	0.1371078E+06	0.1443866E+06	0.1520517E+06
6	0.1363292E+06	0.1454387E+06	0.1551567E+06	144176.	0.1375967E+06	0.1457067E+06	0.1542944E+06
7	0.1368756E+06	0.1468170E+06	0.1574804E+06	145134.	0.1374655E+06	0.1463093E+06	0.1557220E+06
8	0.1374779E+06	0.1482083E+06	0.1597760E+06	145651.	0.1381333E+06	0.1477137E+06	0.1579584E+06
9	0.1381267E+06	0.1496128E+06	0.1620538E+06	147187.	0.1389956E+06	0.1492912E+06	0.1603494E+06
10	0.1388153E+06	0.1510306E+06	0.1643206E+06	148213.	0.1395445E+06	0.1505035E+06	0.1623229E+06
11	0.1395385E+06	0.1524618E+06	0.1665818E+06	150113.	0.1407747E+06	0.1524282E+06	0.1650462E+06
12	0.1402928E+06	0.1539066E+06	0.1688415E+06	151798.	0.1418509E+06	0.1541696E+06	0.1675579E+06
		CONSUMER				CONSUMER	
1	0.7838487E+05	0.7989025E+05	0.8142450E+05	79781.	0.7850800E+05	0.8004694E+05	0.8161587E+05
2	0.7760156E+05	0.8015575E+05	0.8279394E+05	80019.	0.7798369E+05	0.8035937E+05	0.8280737E+05
3	0.7690812E+05	0.8054462E+05	0.8435300E+05	80482.	0.7766919E+05	0.8083650E+05	0.8413294E+05
4	0.7632881E+05	0.8098400E+05	0.8592300E+05	80432.	0.7741750E+05	0.8133987E+05	0.8546087E+05
5	0.7576306E+05	0.8137337E+05	0.8739919E+05	80013.	0.7715587E+05	0.8180756E+05	0.8673969E+05
6	0.7503631E+05	0.8151794E+05	0.8855950E+05	80462.	0.7689137E+05	0.8222762E+05	0.8793412E+05
7	0.7468031E+05	0.8200006E+05	0.9003712E+05	82141.	0.7672275E+05	0.8270800E+05	0.8916006E+05
8	0.7455037E+05	0.8267631E+05	0.9168781E+05	83638.	0.7725106E+05	0.8390662E+05	0.9113544E+05
9	0.7441331E+05	0.8329812E+05	0.9324362E+05	85132.	0.7743475E+05	0.8470350E+05	0.9265450E+05

10	0.7446094E+05	0.8408669E+05	0.9495669E+05	86068.	0.7740969E+05	0.8524344E+05	0.9386987E+05
11	0.7455012E+05	0.8488881E+05	0.9666112E+05	87131.	0.7746450E+05	0.8584469E+05	0.9513144E+05
12	0.7453250E+05	0.8553894E+05	0.9817062E+05	88339.	0.7754387E+05	0.8645012E+05	0.9637919E+05
		DD				DD	
1	0.1399920E+06	0.1456624E+06	0.1515623E+06	145843.			
2	0.1405819E+06	0.1487017E+06	0.1572904E+06	150593.			
3	0.1447517E+06	0.1550569E+06	0.1660956E+06	159275.			
4	0.1421423E+06	0.1538903E+06	0.1666092E+06	152425.			
5	0.1363996E+06	0.1479707E+06	0.1617091E+06	146614.			
6	0.1328068E+06	0.1463724E+06	0.1613235E+06	150064.			
7	0.1352532E+06	0.1502350E+06	0.1668762E+06	149520.			
8	0.1323100E+06	0.1480356E+06	0.1656299E+06	152726.			
9	0.1343711E+06	0.1513693E+06	0.1705177E+06	153654.			
10	0.1322417E+06	0.1499336E+06	0.1699921E+06	153103.			
11	0.1298267E+06	0.1481004E+06	0.1689459E+06	153427.			
12	0.1302696E+06	0.1401781E+06	0.1715190E+06	149962.			
		TD				TD	
1	0.3102527E+06	0.3171117E+06	0.3241220E+06	315858.	0.3117472E+06	0.3186547E+06	0.3257150E+06
2	0.3093614E+06	0.3198437E+06	0.3306809E+06	318276.	0.3128030E+06	0.3228076E+06	0.3331317E+06
3	0.3090084E+06	0.3222769E+06	0.3361149E+06	321139.	0.3129128E+06	0.3253242E+06	0.3382274E+06
4	0.3167807E+06	0.3327827E+06	0.3495929E+06	328965.	0.3231722E+06	0.3380975E+06	0.3537117E+06
5	0.3180627E+06	0.3362441E+06	0.3554644E+06	335100.	0.3242806E+06	0.3411267E+06	0.3588477E+06
6	0.3195549E+06	0.3397397E+06	0.3611996E+06	340802.	0.3255811E+06	0.3441972E+06	0.3638773E+06
7	0.3206983E+06	0.3427268E+06	0.3662681E+06	344314.	0.3274776E+06	0.3477816E+06	0.3693440E+06
8	0.3227346E+06	0.3465644E+06	0.3721535E+06	345154.	0.3287326E+06	0.3505948E+06	0.3739106E+06
9	0.3238392E+06	0.3493199E+06	0.3768051E+06	346783.	0.3299487E+06	0.3532913E+06	0.3782849E+06
10	0.3253226E+06	0.3524137E+06	0.3817604E+06	349010.	0.3333564E+06	0.3582817E+06	0.3850703E+06
11	0.3262388E+06	0.3548347E+06	0.3859369E+06	351308.	0.3346774E+06	0.3609864E+06	0.3893631E+06
12	0.3271489E+06	0.3571968E+06	0.3900042E+06	352258.	0.3361976E+06	0.3638631E+06	0.3938048E+06

Table 11.4 (continued)

	Univariate Model Forecasts				Transfer Function Model Forecasts		
Periods Ahead	95 Percent Lower Confidence Limit	Point Forecast	95 Percent Upper Confidence Limit	Actual Value	95 Percent Lower Confidence Limit	Point Forecast	95 Percent Upper Confidence Limit
		PM					
1	0.1059557E+06	0.1131614E+06	0.1208569E+06	112300.			
2	0.1042018E+06	0.1143627E+06	0.1255142E+06	117000.			
3	0.1013063E+06	0.1135343E+06	0.1272381E+06	116200.			
4	0.9988581E+06	0.1153684E+06	0.1332509E+06	118900.			
5	0.9903731E+06	0.1172667E+06	0.1388513E+06	119800.			
6	0.9763987E+06	0.1181409E+06	0.1429462E+06	113600.			
7	0.9640512E+06	0.1198300E+06	0.1489468E+06	106600.			
8	0.9547031E+06	0.1215433E+06	0.1547367E+06	109200.			
9	0.9474987E+06	0.1232811E+06	0.1604035E+06	106600.			
10	0.9419181E+06	0.1250437E+06	0.1660009E+06	104400.			
11	0.9376206E+06	0.1268316E+06	0.1715643E+06	104200.			
12	0.9343706E+06	0.1286449E+06	0.1771192E+06	107900.			

As expected, the one-period-ahead forecasts were extremely accurate for all three bank groups. The value of time-series analysis for this type of forecasting is unquestionable. However, the twelve-month-ahead forecast errors are a bit larger than anticipated or hoped for. However, most of the error comes as a result of extremely large forecast errors for one or two variables. For most of the variables the forecasts were surprisingly accurate. The median forecasting error for the twelve-month-ahead forecasts for bank groups 1, 2, and 3 were a very acceptable 5.9 percent, 3.2 percent, and 4.0 percent.

Essentially, the average forecast errors were inflated because we were never able to develop a model for PM that forecast with reasonable (under 10 percent error) accuracy. The average forecast error would be as much as 35 percent lower if the errors for PM were not included in the calculations. The problem, though it was not obvious when one looked only at the eighty-seven modeling observations but was apparent by looking at the entire ninety-nine data points, was that PM was not stationary throughout the entire period. The series could not be made stationary either by differencing or by modeling it with various exogenous variables. Given the institutional changes in the federal funds market and its relative newness, this result is not hard to believe. Since the apparent structural changes occurred so late in the sample, we were unable to reestimate a model for PM using either intervention analysis or separate data segments.

Although we suspected that the grouping of banks would alleviate much of the problem, the issue of stability was of major concern throughout this study. During the period covered in the sample, July 1968 to September 1976, numerous shocks were felt throughout the economy. It was fairly clear from the outset of the study that the portfolio items that were subject to fewer and smaller shocks would yield better forecasts. In fact, the most stationary items, TD and DD, yielded extremely accurate forecasts. What was surprising was the relative robustness of the forecasts for the less stable series. The modeling of a bank using intervening variables, local exogenous variables, and knowledge of that particular bank would be a worthwhile effort to improve the accuracy of the forecasts. The efficiency and quality of the forecasts would also be enhanced if the bank's portfolio was estimated simultaneously using a vector valued autoregressive moving the average model.

Given the greater difficulty in modeling the transfer function, the forecast results indicate that the univariate models might well be preferred to multiple-input models. In any event, the use of more than two inputs does not seem called for. For actual forecasting the macro variables values could be generated from univariate models or obtained from other forecasting models (Pierce and Craine).

One of the conclusions that this study seems to imply, that macro variables have little, if any, influence on bank portfolios, is counter to most intuition and economic theory. However, this result was not completely unexpected given the results of other studies (Pierce 1977; Cramer and Miller 1976). Pierce's explanation of this apparent widespread independence seems applicable to our study. Basically, given the fact that the economy offers a miserable experimental design, we cannot verify or refute the relationship between macro variables and bank assets and liabilities. All I am saying is that, for the period in question, macro variables do not add greatly to the explanatory power compared with univariate models.

This chapter has shown that time-series analysis is, and can further be, an important tool for bank portfolio forecasting and analysis. By further disaggregating bank groups and portfolio items and by using information based on knowledge of the particular banks, time-series analysis can be even more valuable in bank analysis.

Appendix

The bank data used in this study are based on Weekly Reporting Bank data compiled by the Federal Reserve Board and the Federal Reserve Bank of San Francisco. Originally the data were for a cross section of 320 banks from 3 July 1968 to 1 September 1976, compiled from weekly reports submitted by large banks to the Federal Reserve describing their conditions. The data were checked for internal consistency and declared to be especially good based on typical microeconomic standards.

To get the data into a form suitable for our study, we carried out three operations. First, we transformed the data into separate time series for each bank. Banks that were not continuous throughout the period were dropped. Next, we combined the weekly data into a monthly average, on the assumption that the most important changes in a bank's balance sheet would be on a monthly basis and that the weekly changes would most likely contain a great deal of noise. Last, we aggregated banks according to three attributes, because of the confidentiality of individual bank data. The traits we aggregated were:

1. Level of assets: (*a*) over $1 billion, (*b*) from $0.5 billion to $1 billion, (*c*) under $0.5 billion).

2. Ratio of time and savings deposits to total assets: (*a*) over 35 percent, (*b*) between 20 percent and 35 percent, (*c*) under 20 percent.

3. Ratio of time and savings deposits to total loans: (*a*) over 1.5, (*b*) between 1.2 and 1.5, (*c*) under 1.2.

Thus there were twenty-seven possible groupings. However, four cells held no banks and three cells were combined with other cells because they held fewer than three banks. This left a total of twenty-two bank groups.