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Time Aggregation, Specification, and
Bank Stock Rates of Return Determination

Elijah Brewer, III
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Time Aggregation, Specification, and Bank
Stock Rates of Return Determination

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ABSTRACT

Stock market data for bank holding companies are used to evaluate the effects of temporal aggregation on coefficient estimates obtained from single- and multi-factor market models. Using multiplicative returns from January 1978 through June 1984, we find that the coefficient estimates of several versions of the market model are generally not independent of the unit of time aggregation. In addition, it is found that temporal aggregation has important effects on both the specification of the market model and the stability of the estimated coefficient. While the three-factor model tends to support most of the notion about the impact of unanticipated changes in interest rates on bank stock returns, it does so with differing quantitative implications and degrees of success as the data is aggregated.

In recent years, stock market data have been used both to evaluate the financial performance of commercial banks, more precisely bank holding companies, and other depository institutions and to provide information about their performance. The primary method of analysis has been based on versions of the single-factor capital asset pricing model specifying the market return on a portfolio of all assets. Studies have used the returns on "bank" stock to gauge the market's risk evaluation of the corresponding bank and changes in the risk evaluation over time, including the likelihood of failure, and to identify the response of banks to changes in particular or general changes in regulation and to nonbank acquisitions. In addition, the basic model has been expanded to include additional factors. In general, either daily, weekly, or monthly rates of return are used to estimate the model coefficients. However, the impacts of temporal aggregation on the model coefficient estimates have not been carefully analyzed.

Based upon Zellner and Montmarquette's (1971) time aggregation technique, Lee and Morimune (1978) have shown that estimates of systematic risk in the single-factor market model are generally not independent of the periodicity of the data used in the empirical analysis. Chen (1980) has shown that ex-ante systematic risk is not invariant under time aggregation when the rates of return are multiplicative. It is shown that the systematic risk regression coefficients will have a mathematical bias which is a function of the unit of time for which empirical data are collected.

The main purpose of this paper is to empirically analyze possible effects of temporal aggregation on the specification of single- and multi-index market models. Return data for the common shares of 71 domestically owned bank holding companies (BHCs) from January 1, 1978 to June 27, 1984 are used to do the related analyses. In the next section of the paper, the model used to investigate the effect of temporal aggregation on the magnitude of the

estimated parameters of the single-factor market model is specified. It is shown that the magnitude of the estimated parameters are generally not necessarily independent of the length of temporal aggregation used. The data and methodology utilized are discussed in section 3. Section 4 presents the results of estimating the single-factor model. The effects of temporal aggregation on the estimation of two- and three-factor market models are evaluated in section 5. The results of this paper are concluded in section 6.

2. Time Aggregation and Systematic Risk

The standard market model (Sharpe (1963)) for the one-period rate of return on security j , $r_{j,1,t}$, can be written as

$$r_{j,1,t} = \alpha + \beta_1 r_{M,1,t} + \epsilon_{j,1,t} \quad (1)$$

$t = 1, 2, \dots, T$

where $r_{M,1,t}$ is the one-period rate of return on the market portfolio in period t , $\epsilon_{j,1,t}$ is a random error term with mean zero and $E(\epsilon_{j,1,t}^2) = \sigma_j^2$ for all t , and β_1 is the systematic risk calculated from one-period data. It is assumed that between periods the rates of return, $r_{j,1,t}$ and $r_{M,1,t}$, have an identical independent distribution. The regression coefficient of the rate of return on security j , $r_{j,1,t}$, with respect to the rate of return on the market portfolio, $r_{M,1,t}$, is given by

$$\hat{\beta}_1 = \text{Cov}(r_{j,1,t}, r_{M,1,t}) / \text{Var}(r_{M,1,t}) \quad (2)$$

Following Zellner and Montmarquette (1971) and Lee and Morimue (1978), the market model in terms of n -period rates of return can be defined as

$$R_{j,n,t} = \alpha + \beta_n R_{M,n,t} + \epsilon_{j,n,t} \quad (3)$$

where

$$R_{j,n,t} = (r_{j,1} \cdots r_{j,n})$$

$$R_{M,n,t} = (r_{M,1} \cdots r_{M,n})$$

$\epsilon_{j,n,t}$ = error term associated with the n-period rates of return on security j in period t, with mean zero variance equal to $\sigma_{\epsilon_j}^2$.

The n-period data regression slope coefficient from equation (3) is given by

$$\hat{\beta}_n = \text{Cov}(r_{j,1} \cdots r_{j,n}, r_{M,1} \cdots r_{M,n}) / \text{Var}(r_{M,1} \cdots r_{M,n}) \quad (4)$$

Levhari and Levy (1977) has shown that the n-period systematic risk associated with multiplicative returns can generally be written as¹

$$\hat{\beta}_n = \frac{[\text{Cov}(r_{j,1}, r_{M,1}) + u_{j,1} u_{M,1}]^n - (u_{j,1} u_{M,1})^n}{(\sigma_{M,1}^2 + u_{M,1}^2)^n - u_{M,1}^{2n}} \quad (5)$$

$$= \frac{\sum_{i=0}^{n-1} a_i \beta_1^{n-i} (1+\alpha)^i}{\sum_{i=0}^{n-1} a_i}$$

where $r_{j,1}$ = one-period rate of return of security j
 $r_{M,1}$ = one-period rate of return of the market portfolio
 $u_{j,1} = E(r_{j,1})$
 $u_{M,1} = E(r_{M,1})$
 $\sigma_{M,1}^2 = \text{Var}(r_{M,1})$

$$a_i = \binom{n}{i} (\sigma_m^2)^{n-i} (u_{m,1}^2)^i$$

$$\alpha = \left[\beta_1 - 1 \right] \frac{u_{m,1} - r_{f,1}}{u_{m,1}}$$

$r_{f,1}$ = one-period riskless rate of return

Levhari and Levy (1977) has shown that the estimated systematic risk obtained from n-period data (β_n) in equation (5) will not be equal to the estimated systematic risk obtained from one-period data (β_1) in equation (2) unless $\beta_1 = 1$. Therefore, the magnitude of the estimated slope coefficient in the single-factor market model is generally not necessarily independent of the length of the temporal aggregation used.

3. Data and Methodology

Daily returns for common stock shares of 71 domestically owned bank holding companies, for the period January 1, 1978 through June 27, 1984, were used to examine the potential biases caused by temporal aggregation. The market portfolio employed in this study was the value-weighted market index (NYSE and Amex) obtained from the Center for Research in Security Prices (CRSP) data base. For each bank holding company the beta coefficient was estimated with daily, weekly, and monthly data.² If $r_{j,1}, r_{j,2}, \dots, r_{j,T}$ are the daily rates of return on security j, one can calculate the weekly rates of returns as

$$R_{j,1} = (1+r_{j,1})(1+r_{j,2}) \dots (1+r_{j,5}) - 1$$

$$R_{j,2} = (1+r_{j,6})(1+r_{j,7}) \dots (1+r_{j,10}) - 1$$

$$\dots$$

$$R_{j,T/5} = (1+r_{j,T-4})(1+r_{j,T-3}) \dots (1+r_{j,T}) - 1$$
(6)

Similarly, the monthly rates of returns can be calculated as

$$\begin{aligned}
 & * \\
 R_{j,1} &= (1+r_{j,1})(1+r_{j,2})\dots(1+r_{j,30}) - 1 \\
 & * \\
 R_{j,2} &= (1+r_{j,31})(1+r_{j,32})\dots(1+r_{j,60}) - 1 \\
 & \quad \cdot \quad \cdot \quad \cdot \quad \dots \quad \cdot \quad \cdot \quad \cdot \quad \quad \quad (7) \\
 & \quad \cdot \quad \cdot \quad \cdot \quad \dots \quad \cdot \quad \cdot \quad \cdot \\
 & * \\
 R_{j,T/30} &= (1+r_{j,T-29})(1+r_{j,T-28})\dots(1+r_{j,T}) - 1
 \end{aligned}$$

Table 1 shows the properties of daily, weekly and monthly rates of return. Mandelbrot (1963) and Fama (1963, 1965) have put forth theoretical arguments and empirical evidence which strongly suggest that security returns conform more closely to stable non-normal distributions. Stable distributions are by definition stable or invariant under addition. This means that if the daily returns on a stock are drawings from a stable distribution, then weekly and monthly returns, which are just sums of the daily returns, have stable distributions of the same "type" as the daily returns. Operationally, if the distributions of daily returns are stable and non-normal, distributions of returns for intervals longer than a day have about the same degree of non-normality as the distributions of daily returns. From table 1, it appears that daily excess rates of return are highly non-normal. The mean studentized range of the daily excess rates of return is 15.1096, compared to a value of 7.80 for the 0.99 fractile of the studentized range of samples drawn from a normal population of size 1000. Mean values of skewness and kurtosis coefficients for daily excess rates of return exceed the value of the 0.99 fractile of the respective distribution under normality. Table 1 indicates that the departures from normality are less pronounced as the unit of time aggregation increases. For example, with weekly data, the skewness and

kurtosis coefficients are less than the values of the 0.99 fractile of the respective distribution under normality. However, while the values of skewness and kurtosis are consistent with normality, the studentized range coefficient is still higher than would be expected under normality. For monthly data, the mean excess rates of return seems close to normal. The values of the studentized range, skewness and kurtosis coefficients are consistent with normality. The implication is that the monthly excess rates of return are close enough to normal for the normal model to be a good working approximation. Nevertheless, these differing results for different units of time aggregation raise the possibility that the degree of misspecification in bank stock study methodologies is sensitive to temporal aggregation. This finding is consistent with the evidence presented by Fama (1976, ch. 1) that daily rates of return data depart more from normality than do monthly rates of return.

4. Single-Factor Market Model Results

Daily, weekly, and monthly data were used to estimate a single-factor version of the market model. The results are shown in Appendix A with the approximate t-ratios given in parentheses. An analysis of the estimated coefficients shows that for 59 out of 71 bank holding companies, the magnitude of the beta coefficients increases as the time unit of aggregation increases. For two bank holding companies (Citicorp and BankAmerica Corporation), the beta coefficients tend to decrease with the time unit of aggregation. The pattern for the last ten cases is not as consistent as that for the previous fifty-nine. There are six cases (Bankers Trust New York Corporation, Land-Mark Banking Corporation of Florida, Manufacturers Hanover Corporation, J. P. Morgan and Company Incorporated, Wachovia Corporation, and Wells Fargo and

Company) showing that the beta coefficients first rising and then falling as the data is aggregated, and four cases (Marine Midland Banks Inc., Old National Bancorporation, Chase Manhattan Corporation, and First Chicago Corporation) showing the reverse. In addition, while all of the coefficients are significantly different from zero at the 5 percent significance level, the t-values consistently decrease for 54 of the bank holding companies as the unit of aggregation increases. Summary statistics for the estimates of beta are given below. Note that while the estimates of beta tend to increase, the interquartile range tends to first increase and then decrease with the level of aggregation. Beta coefficients can generally be used to determine whether a stock is a defensive, neutral or aggressive stock. Our results indicate that bank holding company stocks are generally either defensive ($B < 1$) or neutral ($B = 1$).

Summary Statistics for the Single-Factor Market Model Estimates
of Beta

<u>Aggregation</u>	<u>Arithmetic Mean</u>	<u>Median</u>	<u>Interquartile Range</u>
Daily	0.4501	0.3810	0.2844
Weekly	0.6159	0.6124	0.2942
Monthly	0.8244	0.7977	0.2827

The table in Appendix A also shows the Durbin-Watson statistics for the single-factor market model regressions. On average, the values of the Durbin-Watson statistics are quite close to 2.00 over all levels of aggregation. The arithmetic mean values of the statistics are 1.867, 1.943, and 2.140 for daily, weekly, and monthly models.

There is a tendency for the average values of the Durbin-Watson statistics to increase with the level of aggregation. It is of perhaps more

interest to observe that on the basis of the lower and upper bounds of the 5 percent points for two parameters and a large sample size of 100 observations ($d_L = 1.57$, $d_U = 1.65$), the test statistics indicate the possibility of negative autocorrelation with greater frequency as the data are aggregated.

These results are consistent with those found by Cartwright and Lee (1986) for lightly traded firms. Because the estimated systematic risk from aggregated data is proportional to the estimated systematic risk from disaggregated data, it has been shown (see Zellner and Montmarquette (1971); Rowe (1976); Lee and Morimune (1978); Chen (1980); and Cartwright and Lee (1986)) that the estimated systematic risk from aggregated data can be larger, equal to, or smaller than that from the disaggregated data. The magnitude of R^2 associated with the disaggregated data and the magnitude and sign of the autocorrelations associated with the dependent and independent variables are critical in determining the magnitude of the proportionality factor relating the estimated systematic risk from aggregated data to that from disaggregated data. The estimated systematic risk from aggregated data tends to be greater than that from disaggregated data the lower the R^2 from the disaggregated data, the higher the autocorrelation in the dependent variable and the lower the autocorrelation in the independent variable as the unit of aggregation increases.

Most of the \bar{R}^2 's increase as the time aggregation increases and most of t-ratios decrease as the time aggregation increases as shown by Zellner and Montmarquette (1971), Rowe (1976), Lee and Morimune (1978), and Cartwright and Lee (1986).

5. A Multi-Factor Market Model

Clearly, omission of explanatory variables that are correlated with the market portfolio can bias the estimated beta parameter. Furthermore, if the

omitted variables are autocorrelated, they can account for autocorrelation in the residuals. Whether systematic risk is affected more as the unit of aggregation increases depends on what happens to the variability of the omitted variables, to their correlation with the market index and the correlation between the omitted variables as the unit of aggregation increases. To assess the effects of model misspecification on the estimated systematic risk coefficient as the data is aggregated, we expanded the basic model to include additional factors.

Several empirical studies suggest that movements in an extramarket factor may increase substantially the explanatory power of the single-factor market model. King (1966) found a significant extramarket source of covariation which was attributable to product-industry class as did Campanella (1972). Farrell (1974) tested for non-industry-related extramarket factors in security returns and found that significant groupings could be defined in terms of growth, cyclical, stable, and oil stocks. Farrell was able to minimize the industry effects found by King by sampling from a broad array of industrial classifications. He concluded that the appropriate model for describing security returns might well include four factors: (1) a market factor, (2) an industry factor, (3) a group factor, and (4) a firm-unique factor. In a subsequent study, Martin and Klemkosky (1976) found significant extramarket covariation in common stock returns related to the stock's membership in a growth, cyclical, stable, or oil group. These group effects accounted for as much as 35 percent of the risk in portfolios containing ten oil stocks and as little as 8 percent in a 10-stock portfolio of cyclical stocks. In a more recent study, Fogler, John and Tipton (1981) estimate a three-factor model for nonfinancial firms and find that common stock returns from groups such as Farrell's stable-cyclical-and-growth were related to interest rates in the

government bond market and to corporate bonds with default risk. Schwert (1981) found that returns on different securities in the same industry are highly correlated. Davidson (1984) and Glascock and Davidson (1985) used an industry factor along with a market factor to describe security returns.

The extramarket factor we considered is an industry stock index. Thus the return generating equation used as a base to detect the effects of temporal aggregation on systematic risk takes the form

$$r_{j,n,t} = \alpha + \beta_1 r_{1,n,t} + \beta_2 r_{2,n,t} + \epsilon_{j,n,t} \quad (8)$$

where $r_{1,n,t}$ represents the n-period rate of return on the market index and $r_{2,n,t}$ represents the n-period rate of return on a bank stock index. β_2 can be interpreted to represent the relative riskiness of a particular bank stock in comparison with the banking industry as a whole.

Automatic Data Processing (ADP) data tape, for the period January 1978 through June 1984, was used to construct a bank industry stock market index. A total of 71 bank holding companies was included in the sample: a list of them is provided in Appendix D to this paper. For each bank holding company, the aggregate market value of the stock was computed each day by multiplying the share prices by the number of common stock shares outstanding. On days dividends were paid, the price is adjusted up by the amount of the dividend for computing the market value that day but not adjusted for computing the market value for the next day.³ The bank industry stock index is computed by summing the individual bank holding company market values and then dividing by the value of that sum in a given base year, taken to be 1981.

A number of empirical studies have compared returns on bank stocks to interest rate changes (Booth and Officer (1985); Flannery and James (1984); and Lynge and Zumwalt (1980)). Lynge and Zumwalt (1980), using several

expanded versions of the market model, found that a large portion of commercial bank equity returns is explained by interest rate indices on corporate debt.⁴ Flannery and James (1984), employing a version of the market model used by Lyngne and Zumwalt, found a statistically significant relationship between bank and S&L common stock returns and unanticipated changes in long-term interest rates. Booth and Officer (1985) extends the previous two research studies by considering the effects of investors' expectations of interest rate changes by using a Meiselman-type (1962) error-learning model of movements in the term structure of interest rates. An error learning approach suggests that interest rate expectations are a function of past and present interest rate forecasting experience. As new information is received about errors made in forecasting the current interest rate, interest rate expectations are adjusted in keeping with the learning process. Booth and Officer results indicate that bank holding company returns are sensitive to unanticipated changes in short-term interest rates and this sensitivity is, in turn, related to the holding company's bank balance sheet composition.

As interest rates have become more volatile and have moved to historically unprecedentedly high levels, the degree in which the interest sensitivity of BHCs assets differ from that of their liabilities caused concern. This gap is related to the exposure of bank equity values to unanticipated changes in market interest rates.⁵

If the duration of the assets exceeds the duration of the liabilities, the bank has a negative gap and is exposed to rising interest rates.⁶ If the duration of the assets is less than that of the liabilities, the bank has a positive gap and is exposed to falling interest rates. Controlling the size of the gap is an important function of bank funds management in responding to

anticipated interest rate movements. In this regard, a bank that expects interest rates to rise will attempt to shorten the duration of its assets and lengthen the duration of its liabilities.⁷ In this way, when the expected interest rate change is realized, the bank will be able to reprice its assets at the higher interest rate without experiencing a higher cost on its sources of funds. Thus, a bank with a positive gap should benefit when interest rates rise, while a bank with a negative gap (duration of its assets greater than the duration of its liabilities) will experience a decline in profits.

The precise effect of an unanticipated change in interest rates on the value of a bank's stock depends both on the magnitude and the direction of the interest rate change and on the magnitude and the direction of the difference or gap between the duration of the bank's assets and that of its liabilities. If the duration of a bank's assets exceeds that of its liabilities, the bank's net worth and stock value will be affected unfavorably by an increase in interest rates that reduces the market value of the assets by more than that of the liabilities, and favorably by a decrease in interest rates. Conversely, if the duration of the bank's assets falls below that of its liabilities, the bank's net worth and stock value will be affected favorably by an increase in interest rates that reduces the market value of the assets by less than that of the liabilities, and unfavorably by a decrease in interest rates. Because different banks are likely to have duration gaps that differ not only in magnitude but also in direction, there need not be a unique relationship between interest rate changes and the return on the stocks of each and every bank. Moreover, because banks can and do change the direction of their gaps through time, the relationship will not even be unique for a particular bank through time. In contrast, Booth and Officer (1985) hypothesized that bank equity values may decrease because of higher than

anticipated interest rates regardless of the bank gap position. In addition, they used aggregate instead of individual bank holding company stock rates of return. Moreover, Booth and Officer (1985) did not directly consider the impact of both temporal and cross-sectional aggregation on their empirical results.

To evaluate the effects of temporal and cross-sectional aggregation in a model that explicitly relates unanticipated changes in short-term interest rates to bank stock returns, we ran regressions of the form

$$r_{j,n,t} = \alpha + \beta_1 r_{1,n,t} + \beta_2 r_{2,n,t} + \beta_3 r_{3,n,t} + \epsilon_{j,n,t} \quad (9)$$

where $r_{3,n,t}$ is a measure of unanticipated changes in interest rates in the n -period. β_3 measures the effect of unanticipated changes in interest rates on bank stock return given its relation to both the market and banking indices.

In order to ensure that the estimation of the relation between bank stock returns and unanticipated changes in interest rates is free from "contamination" resulting from changes in default premia, only interest rates on U.S. Treasury obligations are used. In addition, 3-month Treasury bills are used as the representative debt instrument because they are also pure discount instruments (that is, they bear no coupons). Unanticipated changes in interest rates were measured, as in Booth and Officer (1985) and Mishkin (1982), by the difference between the actual 3-month Treasury bill rate in time t and the forward 3-month Treasury bill rate embedded in the yield curve at time $t-1$, $({}_tR_3 - {}_tF_{3,t-1})$.⁸ ${}_tR_3$ is the actual yield in time t on a 3-month Treasury bill and ${}_tF_{3,t-1}$ is the forward 3-month Treasury bill rate calculated in time $t-1$.⁹ The forward rate incorporates expectations and, in equilibrium, this rate is the market forecast of the

expected rate for period t .¹⁰ If the market forecast error, $r_{3,n,t}$, is negative in time period t , (${}_tR_3 - {}_tF_{3,t-1} < 0$), bank equity values may increase or decrease, depending on whether the bank has a positive or negative duration gap.

Tests were conducted to see whether the bank industry and interest rate factors were correlated with the market return factor. Table 2 presents simple correlation coefficients among all three factors. In general these factors are correlated with one another. This presents the problem of multicollinearity in the models to be estimated. Multicollinearity increases the standard errors of the estimated coefficients (lowering the t -values) and may cause some coefficient values to appear to be not significantly different from zero. This makes difficult the identification of individual factors which offset bank stock returns. Because of this, several studies (see Lloyd and Shick (1977); Lyngé and Zumwalt (1980); Flannery and James (1984); and Booth and Officer (1985)) have used orthogonalizing procedures to remove the multicollinearity. The procedures used were equivalent to using only the residuals from a regression of the return on the second factor against the other explanatory variable or variables. Such orthogonalization procedures are equivalent to a transformation which extracts away the common dependence between the variables, assigning such dependence to the explanatory variables in each orthogonalizing regression equation. This procedure will change the OLS estimators and their standard errors on the variables which are orthogonalized, but it does not add any additional explanatory power. For example, if the true equation is

$$r_{j,t} = \alpha + \beta_1 r_{1,t} + \beta_2 r_{2,t} + \epsilon_{j,t}$$

but

$$r_{j,t} = \alpha + b_1 r_{1,t} + b_2 r_{2,t}^* + \epsilon_{j,t}$$

is estimated. Where

$$r_{2,t}^* = r_{2,t} - [\text{Cov}(r_{1,t}, r_{2,t}) / \text{Var}(r_{1,t})] r_{1,t}$$

It can be shown that $\beta_1 \neq b_1$ but $\beta_2 = b_2$. It also can be shown that the standard errors will change for all but the second factor, $r_{2,t}$ (see Giliberto (1985)). Unless there is an economic rationale behind the choice of which variables are orthogonalized, subsequent interpretation of the results is difficult (see Fogler and Ganapathy (1981)). Thus, adjustments were not made to orthogonalize the three factor variables.

Estimates of β_1 and β_2 from the two-factor model of equation (8) for daily, weekly, and monthly data are shown in Appendix 8. The results indicate that in general the banking industry factor is important in explaining bank stock returns. Changes in the stock market index explain, on average, 8, 14, and 23 percent of the variation in bank holding company returns for daily, weekly, and monthly data (see Table 3). The industry stock index contributes another 5, 5, and 15 percent for daily, weekly, and monthly data. The industry stock index tends to dominate the stock market index as the unit of time aggregation increases, suggesting that the industry stock index reflects the market index and perhaps some other unidentified risk factors specific to banking organizations. The table below shows that the pattern of behavior of β_2 , the extra market sensitivity, over alternative levels of aggregation is quite different from that of the beta estimates in the single-factor market model. Specifically, the magnitude of the estimates tends to first decrease and then increase as the data are aggregated. The pattern of the interquartile range is similar to that of β_2 . In comparison, the estimated

coefficients on the market portfolio first increase and then decrease, while the interquartile range tends to increase with the level of aggregation.

Summary Statistics for the Two-Factor Market Model
Estimates of β_2

<u>Aggregation</u>	<u>Arithmetic Mean</u>	<u>Median</u>	<u>Interquartile Range</u>
Daily	0.5302	0.4450	0.3373
Weekly	0.3561	0.3178	0.2411
Monthly	0.6573	0.6006	0.3729

An analysis of the residuals from the two-factor models suggests that the possibility of negative autocorrelation increases with the level of aggregation. The frequency of relatively large Durbin-Watson statistics (40) is more pronounced than in the single-factor model (19).

Summary Statistics for the Two-Factor Market Model
Estimates of β_1

<u>Aggregation</u>	<u>Arithmetic Mean</u>	<u>Median</u>	<u>Interquartile Range</u>
Daily	0.0589	0.0475	0.1079
Weekly	0.3920	0.4020	0.2134
Monthly	0.2810	0.2849	0.3438

While these results provide some evidence to indicate the presence of a second factor, the evidence shows that the disturbances are frequently autocorrelated the more aggregated the data.

Equation (9) is estimated for all 71 bank holding companies over the sample periods using daily, weekly, and monthly data. The results are shown in Appendix C. The estimated coefficients on the market index, β_1 and those for the industry index, β_2 , are not significantly different

Number of Occurrences of Estimates of β_3 Significantly
Different from Zero at the 5 Percent Significance Level
for Equation (9)

Daily
28

Weekly
13

Monthly
9

from those reported in Appendix B for the two-factor model. Changes in the stock market index and the bank industry index explain, on average, 13, 19, and 38 percent of the variation in bank holding company returns for daily, weekly, and monthly data (see Table 3). The evidence reported in Table 3 indicates that the adjusted R-squared coefficients for the three-factor models are at least marginally greater than those for the two-factor models. The estimated values of β_3 , the coefficient on the interest rate forecast error, are significantly different from zero for 28 of the bank holding companies using the 5 percent significance level for the daily model. The coefficient estimates indicate the importance of interest rate forecast in thirteen cases for the weekly model and nine cases for the monthly model. These results imply that time aggregation will generally reduce the chance of detecting the impact of unanticipated changes in interest rates on stock rates of return. In addition, the coefficient associated with the banking industry index rate of return increases with the unit of aggregation. In sum, the relative magnitude of the coefficients associated with r_1 , r_2 and r_3 are not independent of the degree of time aggregation.

The Durbin-Watson statistics indicate that in general the monthly model is not well specified. The test statistic indicates the presence of first-order autocorrelation in 26 cases. For the daily and weekly models, the problem of autocorrelation appears to be less severe. The null hypothesis is rejected at the 5 percent level one time for both daily and weekly models.

The estimates of the coefficients in equation (9) were also obtained by pooling the time series observation for the 71 bank holding companies over each unit of time aggregation. The total time-series/cross-section sample was 116,582, 23,927 and 5,538 for daily, weekly and monthly data, respectively. The model assumes that the coefficients are the same for all bank holding companies. Estimation of equation (9) with pooled cross-sectional time-series data and ordinary least-squares (OLS) is potentially inefficient due to the possibility of firm specific differences in unsystematic risk and time varying unsystematic risk for all firms in the industry. To allow for the possibilities of heteroscedasticity, contemporaneous correlation between the cross-section and serial correlation in unsystematic risk, a version of generalized least-squares (GLS) developed by Fuller and Battese (1974) was used to estimate the cross-sectional time-series model.¹¹ The results of estimating the three-factor model using the Fuller-Battese method are presented in Appendix C.

An examination of the estimates for the pooled cross-sectional time-series data indicates that the coefficient of $r_{3,n,t}$ is significantly different from zero at the .05 level of significance for all levels of aggregation. In addition, the size of the coefficient increases with the level of time aggregation. The results reported for monthly data are consistent with Booth and Officer (1985) findings that bank holding company stocks exhibit an extramarket sensitivity to unanticipated changes in short-term interest rates.¹² The results presented in the current paper are significant because they imply that unanticipated changes in interest rates are still important in explaining bank security returns even after accounting for economywide and industrywide risk sensitivities. While individual bank data suggest that the chance of detecting the impact of unanticipated changes in market interest rates on bank stock rates of return diminishes with the

level of time aggregation, cross-sectional time-series results indicate that the opposite is true, reflecting the impact of cross-sectional aggregation on the results. Estimation of the cross-section time-series equation implicitly assumes that the impact of unanticipated changes in market interest rates on equity values of banks with positive gaps is indistinguishable from that of banks with negative gaps. The individual bank results provide a direct test of the quantitative importance of unanticipated changes in market interest rates on bank equity values, and allow us, at some future date, to relate this to individual bank balance sheet composition.

7. Conclusions

In this study, return data on 71 bank holding companies are used to investigate the effects of temporal aggregation on the particular characteristics of the stock return data and the estimated slope coefficients in single- and multi-factor versions of the market model. The results indicate that the departures from normality are less pronounced as the unit of time aggregation increases. The monthly excess rates of return are close enough to normal for the normal model to be a good working approximation. autocorrelation and variation in daily rates of return of each of the factors have a significant impact on the magnitude of the estimated coefficients in the various models. Specifically, the estimated slope coefficients from aggregated data tends to be greater than that from disaggregated data the lower the R^2 from the disaggregated data, the higher the autocorrelation in the dependent variable and the lower the autocorrelation in the independent variable as the unit of aggregation increase. The problems associated with the estimation of market models to evaluate the financial performance of bank

holding companies and to identify the response of these firms to changes in particular or general changes in regulation and to nonbank acquisitions will not be free from the effects of temporal aggregation. For example, the results imply that time aggregation will generally reduce the chance of detecting the effect of unanticipated changes in interest rates on individual bank stock rates of return. In addition, the coefficient associated with the bank industry index rate of return increases with the unit of aggregation. The results suggest that the relative magnitude of the coefficients associated with the stock market index rate of return, bank industry index rate of return, and the interest rate factor are not independent of the degree of time aggregation. The conclusion is that a researcher cannot choose arbitrarily the time units for which rates of return are calculated because the assumed unit of time aggregation has a crucial affect on estimates of the slope coefficients in the single- and multi-factor market models.

Footnotes

¹This assumes that the market rates of return are independently distributed. If the market rates of return are identically, but not independently distributed, then Chen (1980) has shown that the n-period systematic risk coefficient can be written as

$$\hat{\beta}_n = \frac{\sum_{i=0}^{n-1} a_i \beta_1^{n-1} (1+\alpha)^i + b_n}{\sum_{i=0}^{n-1} a_i + C_n}$$

where b_n and C_n represent the effects of autocorrelation in the market rates of return on $\text{Cov}(r_{j,1}, \dots, r_{j,n}, r_{1,1}, \dots, r_{1,n})$ and $\text{Var}(r_{1,1}, \dots, r_{1,n})$, respectively.

²The equations were estimated using excess returns. The rates of return on the riskless asset used for these calculations were taken to be the rates of return on three-month Treasury bills.

³This procedure is similar to that used to construct the CRSP Value weighted market index. Dividends are included in the CRSP Value-weighted market index.

⁴Inclusion of interest rates as a separate factor can be justified by specifying an intertemporal capital asset pricing model, where the investment opportunity set is permitted to vary and the level of interest rate describes changes in the opportunity set (See Merton (1973)).

⁵For discussion of gap management, see Brewer (1985).

⁶Duration is a measure of the present-value-weighted effective maturity of a security. In its simplest form, duration is computed by (1) multiplying the length of time to each scheduled payment of a default-and option-free security by the present value of that payment, (2) summing over all payments, and (3) dividing by the total present value (or price) of the security. For a discussion of duration see Bierwag and Kaufman (1985), Kaufman (1984) and Bierwag, Kaufman and Toevs (1983).

⁷The term structure may contain a liquidity premium. Toevs (1983) has noted that if such a liquidity premium exists and is positive, one would wish to be somewhat shorter in the times to liability repricing than otherwise would be the case. Nevertheless, conditional on the current value of the liquidity premium, the banks' assets and liability position is still one that depends on the bank's interest rate forecast.

Footnotes (Cont'd)

⁸A number of researchers have measured unanticipated changes in interest rates by the change in the 3-month Treasury bill rate from the previous period, $({}_tR_3 - {}_{t-1}R_3)$. Booth and Officer (1985) have shown that experiments using this measure of unanticipated changes in interest rates led to marginally worse fits for their regression equations, smaller interest rate sensitivity estimates and no appreciable differences as to the statistical significance of any of the other coefficients in the equations. For these reasons, $({}_tR_3 - {}_tF_{3,t-1})$ is used as a measure of unanticipated changes in interest rates rather than $({}_tR_3 - {}_{t-1}R_3)$. Equation (9) was reestimated using changes in the 3-month Treasury bill rate as a measure of unanticipated changes in interest rates rather than $({}_tR_3 - {}_tF_{3,t-1})$, and no significant differences in bank stock pricing were revealed.

⁹The forward 3-month Treasury bill rate embedded in the current term structure of interest rates can be calculated as follows:

$${}_{t+1}F_{3,t} = \frac{(1 + {}_tR_6)^2}{(1 + {}_tR_3)} - 1$$

where ${}_{t+1}F_{3,t}$ is the forward 3-month Treasury bill rate embedded in the yield curve at time t ; ${}_tR_6$ is the current yield on a 6-month Treasury bill in time t ; and ${}_tR_3$ is the current yield in time t on a 3-month Treasury bill.

¹⁰See Hicks (1946) for a discussion of this point, pp. 135-140; pp. 146-147. Fama (1976), in a more recent article, also makes this point.

¹¹Equation (9) was reestimated without the bank industry stock index, and the coefficients of $r_{3,n,t}$ were essentially unchanged from those found in the three-factor model.

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Table 1

Summary of
Time Series Properties of Bank Stock Rates of Return Data

Each number reported in the table is based on the average of
the 71 estimates

	<u>Mean</u>	<u>Standard Deviation</u>	<u>Skewness</u>	<u>Kurtosis</u>	<u>Studentized Ranges</u>
Daily	0.0002	0.0150	0.8464	26.4740	15.1096
Weekly	0.0009	0.0352	0.4837	3.6964	8.2459
Monthly	0.0041	0.0774	0.2992	1.4646	5.4810

Upper Percentage Points: Various Samples
Drawn from a Normal Population

<u>Variable</u>	<u>0.95</u>			<u>0.99</u>		
	<u>100</u>	<u>200</u>	<u>1400</u>	<u>100</u>	<u>200</u>	<u>1400</u>
Skewness	0.152	0.078	0.012	0.321	0.162	0.023
Kurtosis	3.77	3.57	3.22	4.39	3.98	3.34
Studentized range (N=100,200 and 1000)	5.90	6.38	7.33	6.36	6.85	7.80

Table 2

Simple Correlation Coefficients
(January 1978 through June 1984)

Daily

	r_1	r_2	r_3
r_1	1.0	0.74*	-0.10*
r_2		1.0	-0.08*
r_3			1.0

Weekly

	r_1	r_2	r_3
r_1	1.0	0.55*	-0.16*
r_2		1.0	-0.13*
r_3			1.0

Monthly

	r_1	r_2	r_3
r_1	1.0	0.67*	-0.30*
r_2		1.0	-0.20***
r_3			1.0

One star indicates that the simple correlation coefficient is significantly different from zero at the 1 percent level. Three stars indicate significance at the 10 percent level.

Table 3

Adjusted R-Squared Coefficients
(All Bank Holding Companies)

Daily

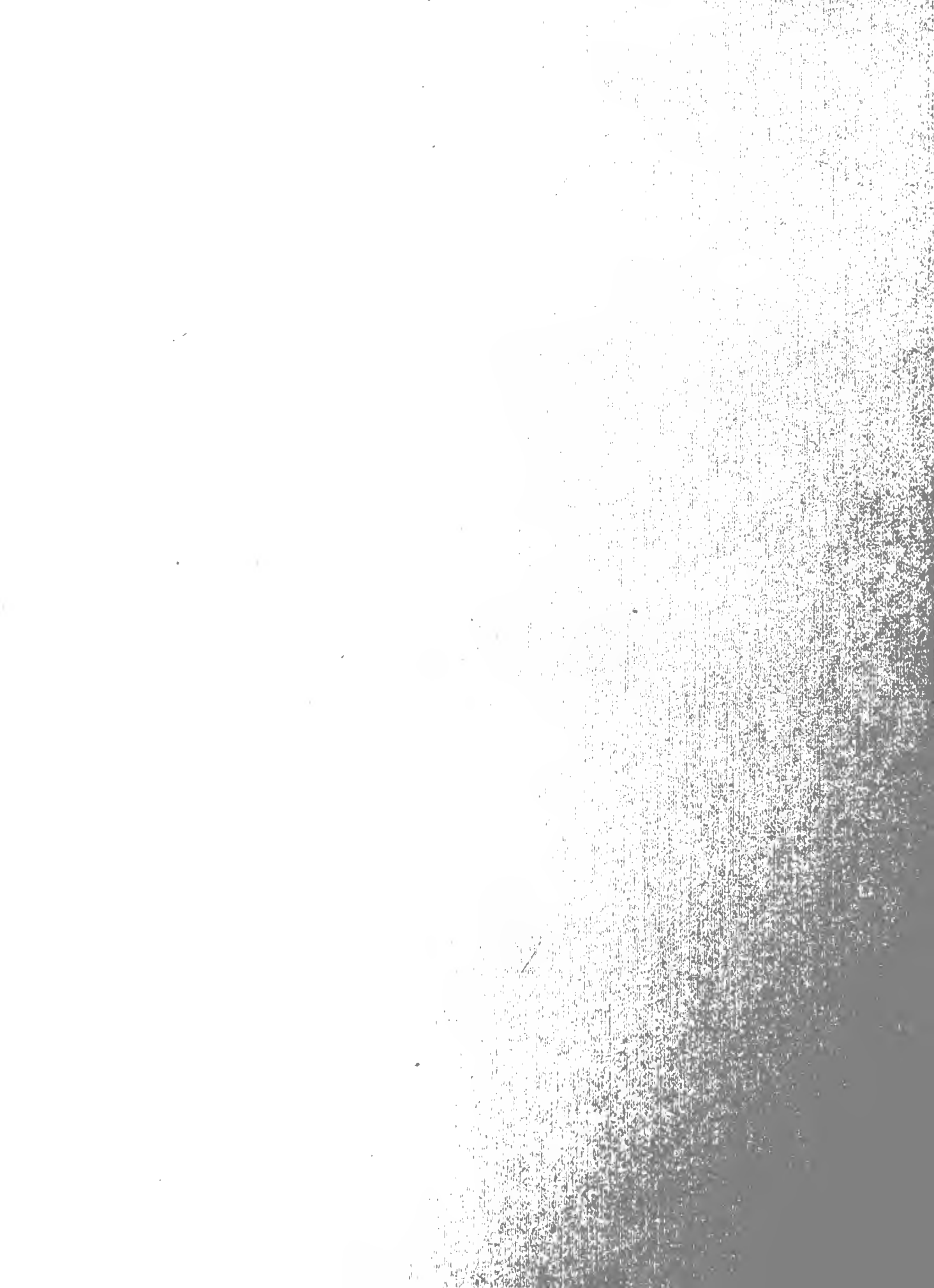
<u>Market Model</u>	<u>Arithmetic Mean</u>	<u>Minimum</u>	<u>Maximum</u>
One-Factor	0.0775	0.0037	0.3121
Two-Factor	0.1317	0.0065	0.6412
Three-Factor	0.1334	0.0073	0.6410

Weekly

<u>Market Model</u>	<u>Arithmetic Mean</u>	<u>Minimum</u>	<u>Maximum</u>
One-Factor	0.1412	0.0194	0.2907
Two-Factor	0.1871	0.0279	0.4534
Three-Factor	0.1894	0.0350	0.4627

Monthly

<u>Market Model</u>	<u>Arithmetic Mean</u>	<u>Minimum</u>	<u>Maximum</u>
One-Factor	0.2305	0.0813	0.4181
Two-Factor	0.3767	0.0962	0.7253
Three-Factor	0.3824	0.1187	0.7224



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