Time-Series Processes of Utility Betas: Implications for Forecasting Systematic Risk

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■ Brigham and Crum [5] describe difficulties with the Capital Asset Pricing Model (CAPM) in estimating utility cost of capital. This controversial article elicited six comments [7, 15, 17, 21, 22, 24], a reply [6], and one extension [11]. Examining the dividend omission by Consolidated Edison (Con Ed), Brigham and Crum note that this information release could confound estimation of Con Ed's beta. Although the Ordinary Least Squares (OLS) beta estimate decreased concurrent with the dividend omission, Brigham and Crum contend that Con Ed's risk had not decreased.

An OLS estimate of beta requires an estimation period during which the relationship between stock return and market return is stable. Without this stability, the forecaster needs alternatives for forecasting a time-varying relationship, such as the general Bayesian adjustment process [25] or its specific variations employed by Merrill Lynch [18]. The appropriateness of a given procedure depends on the particular time-series properties of the beta being forecast.

Information on the time-series properties of utility betas, including the variability of beta and the tendency of utility betas to auto-regress toward an underlying mean, is presented here. The degree of difficulty in forecasting beta depends on both of these properties. Since the basis of Bayesian adjustment lies in beta's tendency to return to an underlying mean, if betas follow a random walk process then Bayesian adjustment will be fruitless.

Collins, Ledolter, and Rayburn [10] explain that random variation in beta leads to severe forecasting difficulties, unlike variability due to auto-regression in beta. To the extent that beta instability is auto-correlated, an unstable beta can be forecasted accurately. Estimating that about 25% of beta variability in their sample is due to auto-correlated beta changes, Collins, Ledolter, and Rayburn suggest that recognition of auto-correlation can improve forecasting accuracy by 15%.

Auto-correlated beta changes allow use of beta adjustment models to improve beta forecasts. A general Bayesian adjustment model would adjust the short-term (transient) beta estimate towards a long-term underlying mean. An example of such an application is the Merrill Lynch [18] adjustment process:

$$B_t = 0.65(B_{t-1}) + 0.35(1.0)\,. \qquad (1)$$

Here, the transient beta estimate obtained by OLS is presumed to return to an underlying mean of 1.0 slowly, since more weight is placed on the transient beta than on the underlying mean.

Studying the time-series properties of utility betas—including their tendency to return to an underlying mean, the speed of this return, and the underlying mean itself—should prove helpful in formulating Bayesian adjustments of beta forecasts. Carleton [7] suggests that Bayesian-adjusted beta forecasts have been applied, often inappropriately, to beta forecasts in regulatory proceedings. This study strives to determine whether such Bayesian adjustment processes are appropriate at all.

I. Beta Coefficient Instability and the Rate-Setting Process

Cooley [12] points out the widespread, albeit controversial, use of the Capital Asset Pricing Model in estimating required return for utility equity. Exchanges published by two journals dealing with the CAPM for rate setting ([7, 15, 17, 21, 22, 24] and [4, 19, 20]) center not on the validity of the theory but on the reliability and usefulness of beta estimates.

Concern over empirical estimates of systematic risk is based on a substantial body of empirical literature pointing to beta instability. From the early descriptive work of Blume [2] through later tests by Fabozzi and Francis [13] and Collins, Ledolter, and Rayburn [10], the evidence supports instability in security betas. Studying specifically the behavior of utility betas, Bey [1], Chen [8], and Pettway [23] all demonstrate instability.

Although the size of beta instability has been extensively investigated, comparatively little attention has been focused on the form of that instability, particularly for utilities. Beta instability does not necessarily preclude application of the CAPM unless combined with a random walk process for beta.

The simplest case, a constant coefficient process for beta, may be expressed as:

$$B_{it} = B_{i,t-1} = B_i^m \text{ for all } t\,. \qquad (2)$$

In Equation (2), the beta at any point in time remains equal to the previous beta and also to a constant underlying mean beta, B_i^m. This constant coefficient process is assumed in OLS estimation of a beta and serves as the null hypothesis in tests of beta variability [3, 13].

When the transient beta for a particular company (B_{it}) is distributed around an underlying mean beta for that company B_i^m, the resulting time-series process may be described as:

$$B_{it} = B_i^m + u_{it}\,. \qquad (3)$$

Equation (3) describes the random coefficient model tested by Fabozzi and Francis [13] and assumed in a beta forecasting model by Chen and Keown [9]. Since the deviations of beta from its underlying mean (u_{it}) are limited to a single period and are serially uncorrelated, the transient beta (B_{it}) tends to return quickly to the underlying mean.

If the transient beta takes more than one period to return to its underlying mean, then an auto-regressive process describes the time-series behavior of beta:

$$B_{it} = a_i B_{i,t-1} + (1 - a_i)B_i^m + u_{it}\,. \qquad (4)$$

This process is very similar to the random coefficient process, except for the strength of the tendency for mean-reversion. A value of 0.9 for $1 - a_i$ would cause the process to be classified as auto-regressive, whereas a value of 1.0 would label it random coefficient. Otherwise, there is little difference.

The auto-regressive model described in Equation (4) is the same one studied by Bos and Newbold [3] and Collins, Ledolter, and Rayburn [10]. The process considers a tendency to return to an underlying mean beta, where the tendency is measured by $1 - a_i$. The Merrill Lynch adjustment process [18] describes a special case in which the underlying mean beta (B_i^m) is 1.0 and the adjustment factor to the mean, also called the regression rate ($1 - a_i$), is 0.35. Vasicek's adjustment model [25] is a less restrictive case in which the underlying mean beta is unity and no restriction is made on the adjustment rate toward the underlying mean.

If all beta variation is random, then there will be no tendency for beta to return to an underlying mean, resulting in a random walk process:

$$B_{it} = B_{i,t-1} + u_{it} . \qquad (5)$$

This model has been suggested as a time-varying model for beta in a stability test described by Garbade and Rentzler [14]. Since there are no bounds on the value that beta can assume, the process is difficult to forecast, especially in the long run. If beta follows a random walk process then the best long-term forecast is the short-term beta, and a Bayesian adjustment process will not improve the forecast. Notably, Brigham and Crum's [6] original criticism of the CAPM was based on unadjusted OLS estimates of Con Ed's beta, which implicitly assumes that an unstable beta follows a random walk.

II. The Beta Coefficient as an Auto-Regressive Variable

Any of the four beta-generating processes can be represented as a special case of a general auto-regressive process. The general model has a measurement equation,

$$R_{it} = B_{it} R_{mt} + e_{it} , \qquad (6)$$

and state equation,

$$B_{it} = a_i B_{i,t-1} + (1 - a_i)B_i^m + u_{it} , \qquad (6')$$

where R_{it} is the excess return on the ith security during time t, R_{mt} is the return on the market index during time t, B_i^m is the underlying mean beta for the ith stock, and B_{it} is the transient beta for the ith stock at time t.

Equation (6') specifies a first-order auto-regressive process for beta. If the value for $1 - a_i$ is 0.0, then (6') reverts to the random walk process described in Equation (5). If the value for $1 - a_i$ is 1.0, then (6') reverts to the random coefficient process described in Equation (3). If the residual variance is 0.0, then $1 - a_i$ becomes 0.0 and the underlying mean and error terms in Equation (6') drop out, leaving the constant beta process in Equation (2).

III. Estimating Parameters of the Model

The parameters of the model in Equations (6) and (6') were estimated using monthly stock return data from the Compustat PDE file for 109 utility companies. 61 electric and 48 electric and gas. The 15-year sample period is from January 1967–December 1981. The period contains both the dividend omission by Consolidated Edison [5] and the Three Mile Island incident.

The model in Equations (6) can be expressed in matrix format as:

$$R_{it} = \underline{h}_t \underline{B}_{mt} + \underline{e}_{it} , \qquad (7)$$

$$\underline{B}_{it} = \underline{A}_i \underline{B}_{i,t-1} + \underline{U}_{it} , \qquad (7')$$

where

$\underline{h}_t = (R_{mt}, 0)$;
$\underline{B}'_{it} = (B_{it}, B_i^m)$;
$\underline{U}'_{it} = (u_{it}, 0)$ and is distributed as $N(0, W_i S_i^2)$,

$$\underline{W} = \begin{bmatrix} w_i & 0 \\ 0 & 0 \end{bmatrix} , \qquad (8)$$

$$\underline{A} = \begin{bmatrix} a_i & 1 - a_i \\ 0 & 1 \end{bmatrix} . \qquad (9)$$

The recursive Kalman filtering approach described by Kahl and Ledolter [16] is used to estimate simultaneously the three parameters of the market model in Equations (6). These parameters are: the underlying mean beta (B_i^m), the regression rate toward the underlying mean ($1 - a_i$), and the variance of beta over time.

Simultaneous estimation of three parameters requires considerable data and computer resources which might explain why studies using broad samples and large numbers of stocks formulate the problem somewhat differently. Bos and Newbold estimated a Kalman filtering model with a two-pass process. Decreasing the number of parameters from three to two reduces the computation time to only a fraction of that required for a full model. Collins, Ledolter, and Rayburn [10] suggest that the procedure followed by Bos and Newbold [3] creates a downward bias in the estimate of beta's regression rate. They were able to eliminate the estimate of the underlying mean beta in the model and focus on beta regression tendencies.

The model used in this study produces independent variance estimates like the model used by Collins, Ledolter, and Rayburn. In addition, this model estimates the underlying mean beta. Maximum likelihood estimates of elements in the transition matrix (a_i), the variance ratio (w_i), and the variance of the measurement equa-

Exhibit 1. Maximum Likelihood Estimates of Model Parameters

Regression Rate	Standard Deviation of Beta 0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.0			2[a]	3[a]	4[a]	6[a]	12[a]	5[a]	3[a]		
0.1				1	2	5	1				
0.2					1	7	2	5	2		
0.3				1	1	2	5	1	3		
0.4				1	2	1	3	1			
0.5											
0.6						1					
0.7						1					
0.8											
0.9		1	1								
1.0	6[b]	17[c]									

[a]These firms display characteristics of firms whose betas follow a random coefficient process.
[b]These firms display characteristics of firms whose betas are constant.
[c]These firms display characteristics of firms whose betas follow a random walk process.

tion (S_i^2), were all concurrently estimated using a grid search procedure.

IV. Results

The particular time-series process followed by a beta can be indicated by two parameters: the standard deviation of this beta over time, u_{it} in Equation (6'); and its adjustment rate to the mean, $(1 - a_i)$ in Equation (6'). Consequently, the cross-tabulation of these two parameters in Exhibit 1 is also a tabulation of the process followed by the beta. The most common process shown in Exhibit 1 is the auto-regressive process. Nearly half of the companies in the sample, 51 out of 109, show a nonzero standard deviation of beta together with a value for the regression rate between zero and unity.

The next most common process is the random coefficient process, indicated by a nonzero value for the standard deviation of beta together with an estimate of 1.0 for $1 - a_i$. These estimates are shown by 35 of the sample companies. The firms with auto-regressive betas and those with very similar random coefficient betas jointly comprise 86 of the 109 sample firms.

A nonzero estimate of the standard deviation of beta combined with a regression rate of zero indicates a beta following a random walk process. Parameter estimates consistent with a random walk process are shown for only 17 companies.

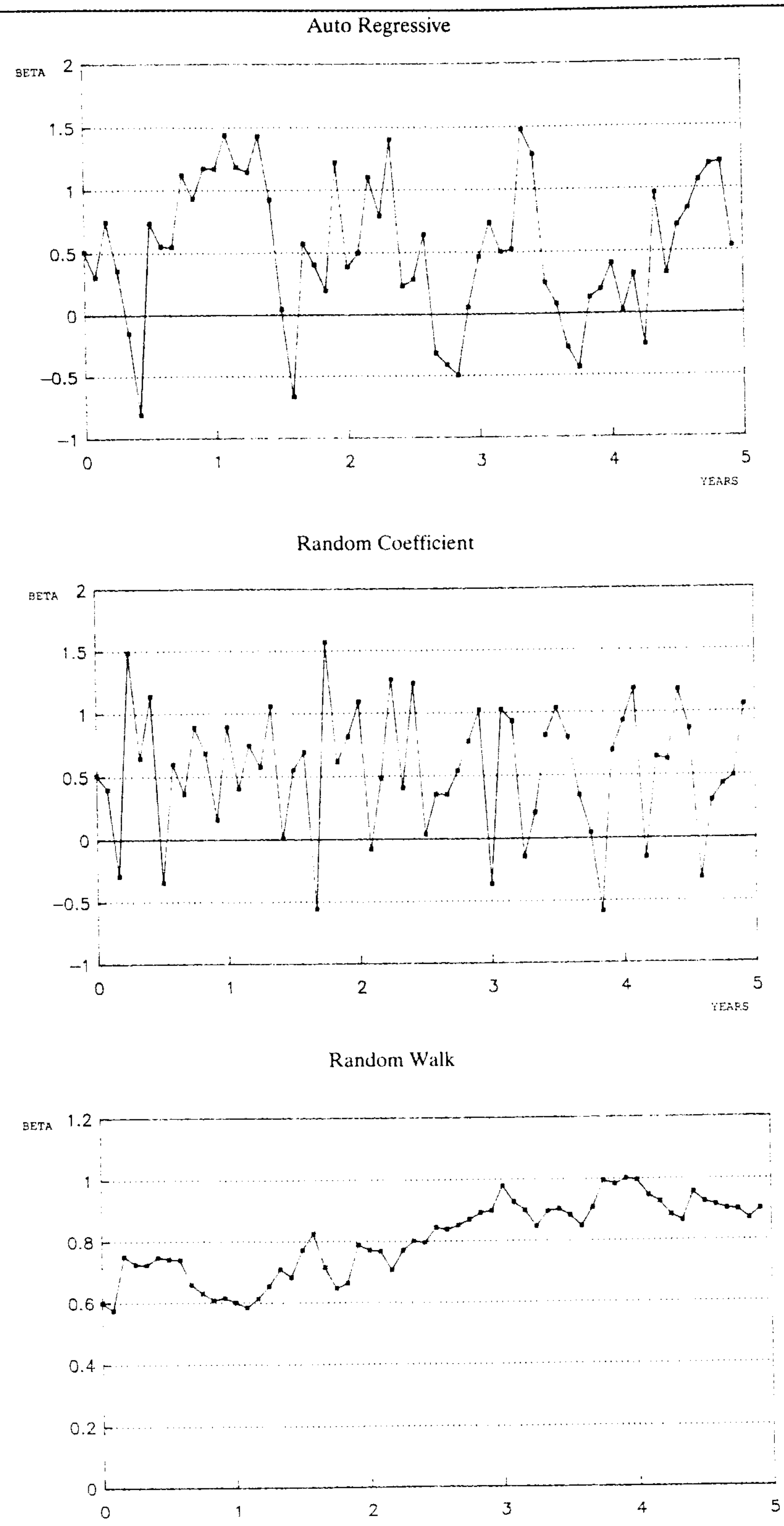
The least common process indicated by companies in the sample is the constant coefficient process, shown by only 6 companies. A constant beta coefficient is indicated by a zero estimate for the standard deviation of beta.

Since the estimation period covers 15 years (180 months), many companies could not maintain a constant beta coefficient. The long estimation period allows management, regulators, and the markets to react to any exogenous changes affecting systematic risk so as to bring risk back to reasonable levels. Such reaction is consistent with a beta that follows an auto-regressive process. Consequently, the preponderance of companies with auto-regressive betas in Exhibit 1 conforms to expected long-term behavior of management and markets.

Internal consistency of parameter estimates in Exhibit 1 is just as important as reasonableness. All companies having a zero estimate for the standard deviation of beta also show a value of 0.0 for the adjustment rate estimate. Any other estimate would be ambiguous for classifying the process. A positive association between the estimate of the standard deviation of beta and the estimate of $1 - a_i$ further points to the lack of ambiguity and helps in interpreting the process for all of the sample companies.

The positive association between beta variability and the regression rate is also consistent with boundaries upon beta values. Companies with high beta variability tend to have betas that return quickly to an underlying mean. Companies with low or zero return rates have low beta variability. High variability to-

Exhibit 2. Three Time-Series Processes for Beta



gether with a low or zero return rate would lead to extreme beta instability and preclude application of the CAPM. The results show no evidence of this type of beta instability.

A. Behavior of Transient Betas

To illustrate the implications of different processes and parameters, plots of betas following an auto-regressive process, a random coefficient process, and a random walk process are presented in Exhibit 2. Each of these processes behaves according to average coefficient values of companies with that process in Exhibit 1. For the auto-regressive process, the coefficients are an underlying mean of 0.51, a standard deviation of transient beta of 0.50, and a return rate toward the underlying mean of 0.52. For the random coefficient process, the underlying mean is 0.52 and its standard deviation is 0.53. For the random walk process the standard deviation of beta is 0.05.

The auto-regressive beta depicted in Exhibit 2 shows considerable variability and ranges between a minimum value of -0.8 and a maximum value of 1.50. Although the variability in the short run is rather large, the beta at no time takes longer than 9 months to return to its underlying mean, usually returning in three or four months. However, upon returning to its underlying mean it often strays on the opposite side, requiring several additional months to return.

Over the 60-month period shown for the auto-regressive process in Exhibit 2, only 36 of the transient beta values fall between a low of 0.0 and a high of 1.0. These bounds might be considered reasonable for a utility. Nine of the 60 beta observations lie below 0.0. The presence of such outliers might frustrate, but not obviate, application of OLS techniques for beta estimation. Although Exhibit 2 indicates that extreme beta values, such as those discussed by Brigham and Crum [5], might be common in the short run, the forecaster should not be deterred by the presence of short-run instability. In the long run, beta will return to its mean.

The similarity between the auto-regressive process and the random coefficient process, also shown in Exhibit 2, is obvious. Even if rather extreme values are encountered, the random coefficient beta reverts back to the mean within the next two observations. The upper and lower bounds on beta as well as the proportion of betas less than zero are very similar for the two processes.

Exhibit 2 also contains a plot of the time-series behavior of a beta following a random walk process. Although the beta behavior for the random walk process seems more stable than the auto-regressive or random coefficient process, such apparent short-run stability is misleading. Over the 60 months depicted in Exhibit 2, the beta wanders from a value of 0.6 to a value of about 0.9. Over the next 60 months, the beta could potentially rise by another 0.3, fall back to 0.6, or be anywhere in between. In the longer run, the beta becomes even more difficult to forecast, due to the lack of any tendency to revert to an underlying mean.

B. Focusing on the Consolidated Edison Dividend Omission

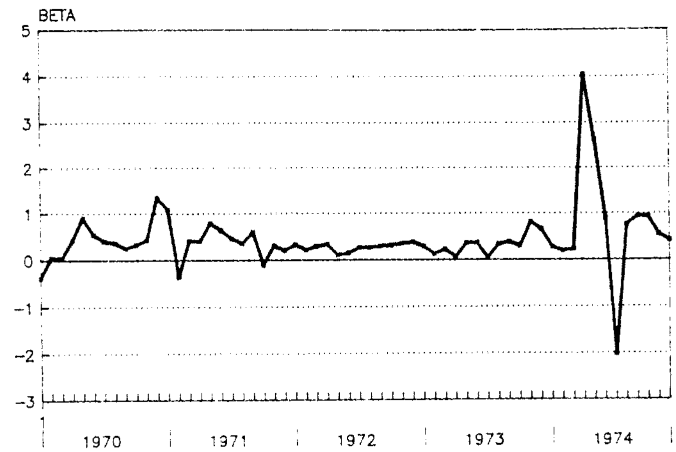
A plot during the period from January 1970–December 1984 of the behavior of the transient beta for Consolidated Edison is presented in Exhibit 3. The transient beta behaves much like the typical beta for any utility with an auto-regressive beta, except for the period immediately following the dividend omission. During this period, the transient beta becomes very erratic for about 9 months. Once it settles down, it continues to behave like any other utility with a typical auto-regressive beta. The plot of the transient beta for Con Ed over the last 60 months, if placed on the same scale as Exhibit 2, would be visually indistinguishable from the auto-regressive process depicted in that exhibit.

The plot of Con Ed's transient beta shown in Exhibit 3 depicts the transitory effect of economic disturbances on beta estimates. Even in this dramatic case of a dividend omission, the relationship between the stock and the market returned to normal within less than one year. This strong tendency to return to the mean beta gives empirical support to forecaster-supplied prior values in Bayesian adjustment models that place more weight on the underlying mean beta and less weight on the transient beta than the Merrill Lynch model would imply.

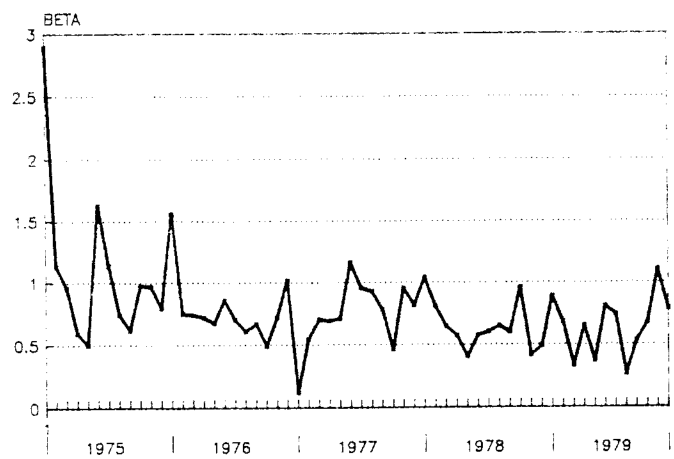
Some additional information on the behavior of Con Ed's beta is presented in Exhibit 4. During the overall period, which extends from January 1970–June 1984, its OLS beta estimate was 0.61 and the estimate of its underlying mean beta was 0.58. Since this overall period contains the dividend omission, a null hypothesis of a constant coefficient process for beta can be easily rejected. The regression rate of 0.70 toward the underlying mean indicates a strong mean-reversion tendency.

Exhibit 3. Transient Beta for Consolidated Edison, 1970–1984

1970–1974



1975–1979



1980–1984

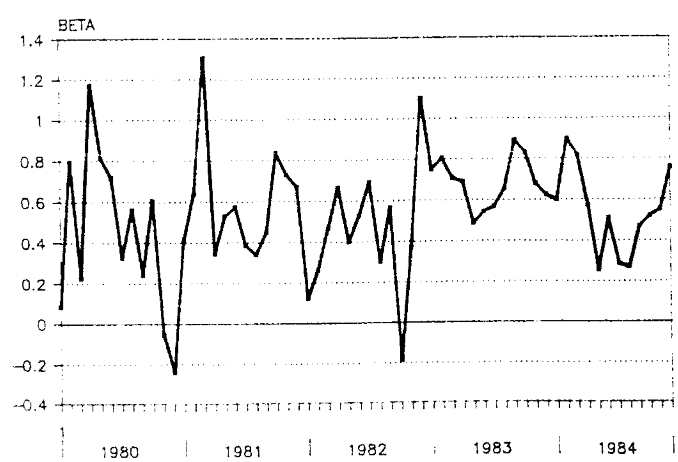


Exhibit 4. Parameter Estimates for Consolidated Edison Beta

Parameter	Overall Period 1970–1984	Before Dividend Omission 1970–1973	After Dividend Omission 1978–1981
Ordinary Least Squares Beta	0.61	0.39	0.62
Standard Error of OLS Beta	0.08	0.04	0.05
$K - F$ Underlying Mean Beta	0.58	0.34	0.47
$K - F$ Regression Rate to Mean	0.70	1.00	1.00
$K - F$ Standard Deviation of Beta	0.74	0.62	0.78
$K - F$ Residual Error in Market Model	0.05	0.03	0.04
$K - F$ Beta Stability Test	58.80*	20.30*	7.00*

*Significant at the 0.05 level.

Exhibit 4 also contains Kalman filtering and OLS estimates of beta for both a four-year period prior to the divided omission and a four-year period after the dividend omission. Forty-eight monthly observations is not sufficient to estimate reliably the underlying mean beta, since by nature this parameter reveals itself only over the long run. Likewise, the estimate of $1 - a_i$ may also be unreliable when estimated by only a few observations over a short time period. However, the subperiods do depict the variability that is characteristic of short-term estimates, whether those estimates are obtained by OLS or by Kalman filtering.

Although these short-term estimates should be approached with caution, some effects of the dividend omission on Con Ed's risk might be inferred. First, estimates for the long-term period or either of the short-term periods do not appear contaminated by the dividend omission but appear quite reasonable for a utility. Second, no indication of a decline in the beta estimate due to inclusion of the dividend omission period is evident. The indication is to the contrary. The estimate of the underlying mean beta for the overall period is higher than either the four- year period prior to the omission or the four years following the omission.

V. Implications for Beta Forecasting and Rate Setting

A partial resolution to the beta measurement problem is outlined by Peseau and Zepp [22], who show that the effect of the dividend omission was transitory and could be diagnosed from examination of OLS statistics. Although the dividend omission produces beta estimation problems for Consolidated Edison, subsequent estimates using data after the omission become much more reasonable.

The primary difference between the Brigham and Crum [5] forecast using an OLS beta and the Peseau and Zepp comment lies in the assumption of the time-series process followed by beta. The OLS estimate for five years of return data is only a good beta forecast if beta follows a constant coefficient process. This assumption is untenable for an estimation period containing a major information release.

When beta is time-varying, a short-term unadjusted OLS estimate may not be the best estimate of beta. Instead, the forecaster, taking advantage of auto-regressive properties of beta, should adjust that short-term estimate toward an underlying mean beta. When beta is unstable but reverts to an underlying mean, beta instability would not preclude application of the CAPM, but might preclude use of an OLS beta.

Reliance on a short-term beta forecast, whether from an OLS estimate or the transient beta estimate in the Kalman filtering model, is appropriate only if the firm's beta follows a random walk process. This research shows little evidence suggesting the typical utility beta follows a random walk and no evidence that, specifically, Con Ed's beta follows a random walk.

Due to the preponderance of auto-regressive or random coefficient betas, the results of this study strongly support the use of Bayesian-type adjustment processes such as the one employed by Merrill Lynch. The results also suggest that the behavior of utility betas may differ from the behavior of large diversified samples of stocks. For example, since Blume [2] finds an underlying mean beta of 1.0 for a large sample of stocks, many Bayesian models will adjust the OLS beta estimate toward 1.0. The results of this study, however, indicate that 1.0 is too high an underlying mean for most utilities. Instead, they should be adjusted toward a value that is less than one. For Consolidated Edison, an underlying mean of 0.7 would be more appropriate.

VI. Conclusions

Understanding beta behavior requires more information than whether or not betas are stable. Development of statistical procedures admitting a continuously time-varying beta now allows forecasters to understand how beta may behave over the short run and how that short-run behavior can differ from long-run behavior. Measuring continuously time-varying betas also frees the forecaster from the limitations imposed by assuming a constant coefficient beta. Instead, like most economic variables, beta can be modeled as a coefficient that is always changing. From the time series process followed by betas, the forecaster also gains an understanding of the difficult problem of forecasting beta. The beta for the majority of utility companies in this sample follows either an auto-regressive process or a constant coefficient process. Very few appear to follow a random walk process, which would produce betas that are not only unstable but very difficult to forecast. On the other hand, with an auto-regressive process, a patient forecaster using relatively simple diagnostic procedures should be able to obtain a reasonable long-run estimate of systematic risk. A reasonable forecast of beta then admits application of the CAPM for utilities even if beta is time varying.

The strong evidence of auto-regressive tendencies in utility betas lends support to the application of adjustment procedures such as the Bayesian adjustment procedure presented by Vasicek [25]. This procedure depends upon beta following an auto-regressive process. In addition, the Kalman filtering methodology also provides objective prior estimates of the underlying mean beta and the adjustment rate toward that underlying mean.

Typical adjustment models use a prior estimate of about 0.35 for the adjustment rate toward the underlying mean and a prior estimate of 1.0 as the underlying mean. The results of this study indicate that an underlying mean of 1.0 is too high for most utilities and an adjustment rate of 0.35 is too low.

Although considerable variability in adjustment rates and underlying mean betas can be observed in the sample, it may not be necessary for a forecaster to apply the Kalman filtering approach in order to obtain these estimates. A reasonable estimate of the underlying mean may be obtained by OLS if applied to a very long time period. The prior estimate of the adjustment rate toward the mean can be obtained by considering the positive relationship between the adjustment rate and beta variability. Estimates of the prior adjustments in the Bayesian adjustment models could be applied without relying blindly on large-sample estimates that may not be applicable to utilities.

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