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RISK INSTABILITY IN THE ELECTRIC UTILITY INDUSTRY

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In recent years the use of the Capital Asset Pricing Model (CAPM) in regulatory hearings for the purpose of estimating the cost of capital to a utility has been increasing. Criticism of its use has been primarily concerned with the presence of instability in the so-called beta coefficient of the model, the presence of which violates conditions necessary to apply the standard estimation procedure of Ordinary Least Squares. Pettway (8) examined a portfolio of thirty six electric utilities between 1971 and 1976, and concluded that instability was a problem for some subperiods, but that there were other times when the evidence was in favor of a stable parameter.

Past studies of beta instability have typically relied on standard econometric techniques that assume a priori knowledge of the point in time of the instable behavior. These techniques may "blind" the researcher to potential instability elsewhere in the time series of returns data examined, and do not generally provide a perspective of relative degrees of instability at different points in the series. We will examine some alternative testing procedures that have the additional advantage of providing visual aids which may serve as heuristic guides to the nature and point in time of instable parameter behavior. These tests will be applied to a portfolio of ninety electric utilities and two individual electric utilities using monthly data for the period 1971-1977. We will establish that a dividend decision by Consolidated Edison of New York (Con Ed) had a profound influence on its own beta coefficient (it did not pay a quarterly dividend for the first time in ninety four years), but that a suspected effect to the industry as a whole is not apparent (relative to the use of monthly data). A final application of the tests will illustrate how the returns data for some firms may be partitioned to provide a recent period where beta is stable and estimation may be conducted.

In section one of the paper we will discuss market models and some of the assumptions which suffice to legitimize the estimation of them as linear models with observable time series data. In section two we define recursive residuals, which can be viewed as transformations of the Ordinary Least Squares (OLS) residuals of either an individual firm or portfolio of firms, and from which statisitics may be formed to test for the presence (not point) of beta instability. Two tests based on recursive residuals, the Cusum and Cusumsquare, are described. Finally, we present a maximum likelihood procedure to aid in detecting the point in time of a possible switch in beta. In section three we proceed to apply the techniques of section two to an analysis of the electric utility industry, and an example of how beta may be estimated for some firms is presented.

I

MARKET MODELS

Section 1.1 The Capital Asset Pricing Model

Since 1964 one of the foremost models produced to explain asset returns has been the Capital Asset Pricing Model (CAPM). The most commonly referred to version is attributed primarily to Sharpe (12), and slightly later to Lintner (6), and Mossin (7).

As stated in an article by Bicksler (1), the basic assumptions underlying the model are:

1. All investors are risk averse and choose portfolios in a manner consistent with maximizing expected utility of single-period terminal wealth.
2. Portfolio investment opportunities can be described solely in terms of means and variances (or standard deviations) of the ex-ante distribution of one-period portfolio returns.
3. Investors have homogeneous expectations regarding means, variances, and covariances of returns for all securities in the investment opportunity set and, in addition, all investors have identical investment opportunity sets.
4. Capital markets are efficient in the sense that borrowing and lending rates are equal. There are no restrictions to short sales, no taxes, no transactions costs, and capital assets are perfectly divisible, et cetera.
5. The supply of all capital assets is given.

The fundamental result is:

$$E(R_i) = R_f + b_i(E(R_m) - R_f)$$

where $E(R_m)$ is the expected return on the market portfolio (of all risky assets)

$E(R_i)$ is the expected return on an individual security for the single period being considered

R_f is the riskless rate of return (for both borrowing and lending)

$b_i = Cov(R_i, R_m)/var(R_m)$ is the systematic risk of the i^{th} security

Major criticisms of the model are that the borrowing and lending assumptions are too restrictive (and do not reflect reality), and that it is necessary to use a proxy (such as the New York Stock Exchange index) for the market return R_m. Ross (11) has derived a market model which results in a "generalized" CAPM in that CAPM is a specific case of it. With little of the "excess baggage" in the way of CAPM assumptions, Ross reproduces the basic form of CAPM in a model which also allows us to use a market index in a context where it is truly a determinant of a firm's ex-ante expected return. We present the basic idea behind this model, known as the Arbitrage Pricing Theory (APT), and reinterpret the model's analogue to R_f. We do this primarily as a means of justifying the estimation procedure we use, which involves using a composite index of market returns in place of R_m.

Section 1.2 The Arbitrage Pricing Theory

As presented in the Ross paper, APT is based on the following arguments: Suppose asset returns are generated by some stochastic relation

$$R_i = E(R_i) + \beta_i \delta + \varepsilon_i; \quad i = 1, 2, \ldots, n .$$

where $E(R_i)$ is a constant term representing the ex-ante expected return

δ is a mean zero common factor (we do not need to specify it, but if CAPM were indeed true it would represent the deviations of the market return from its expected value).

$\varepsilon = (\varepsilon_1, \ldots, \varepsilon_n)$ is a mean zero noise vector

We now form an arbitrage portfolio η of the n assets. Here η is an n by 1 vector of asset proportions with the property that $\eta'e = 0$, where e is the n by 1 vector $(1, 1, \ldots, 1)'$. In this portfolio, the wealth invested in long assets is exactly balanced by the amount borrowed from short sales and, net, the portfolio uses no wealth. The portfolio is also chosen in a well diversified manner to permit us to use the law of large numbers to approximately eliminate the noise term $\eta'\varepsilon$, and in such a fashion that it eliminates systematic risk as well ($\eta'\beta = 0$). Thus the portfolio return R_p is:

$$R_p = \eta' R = (\eta' E) + (\eta'\beta)\delta + \eta'\varepsilon$$

$$\cong (\eta'E) + (\eta'\beta)\delta$$

$= \eta'E$ where E is the vector of ex-ante mean returns, R the vector of returns

The model is named Arbitrage because in place of the primary assumptions of CAPM, it simply requires that arbitrage opportunities not exist, i.e. the ability to make money from a zero wealth portfolio be disallowed. Since η is a zero wealth portfolio we must have

$$R_p = \eta'E = 0, \text{ or}$$

$$\eta'\beta = \eta'e = 0 = \eta'E = 0,$$

and this in turn implies that E must be a linear combination of e and β. So we can write

$$E(R_i) = E_o + a\beta_i$$

By forming the market portfolio α_m on E we get

$$\alpha_m E = E(R_m) = E_o + a \text{ (having normalized } \alpha_m\beta = 1)$$

so $a = E(R_m) - E_o$ and $E(R_i) = E_o + (E(R_m) - E_o)\beta_i$,

which is the arbitrage equivalent of CAPM.

Assuming this could all be achieved among firms listed in the market return index we use below, then $E(R_m)$ can be interpreted as that index. Also E_o, which is analogous to R_f in CAPM, can be interpreted as the return which any zero beta portfolio α_p (i.e. $\alpha_p\beta = 0$) will yield.

If an R_f does exist, then Ross shows that $R_f = E_o$.

Section 1.3 Applying the Models in Practice

In application we normally make a further assumption about CAPM or APT in order to convert the equilibrium (or expectations) form of the model into a model providing observable time series data for estimation purposes. In CAPM we usually assume that

$$\text{(i)} \quad R_i = E(R_i) + b_i(R_m - E(R_m)) + e_i$$

Plugging the CAPM valuation of $E(R_i)$ into (i) yields

$$\text{(ii)} \quad R_i = (1 - b_i)R_f + b_iR_m + e_i$$

This model is estimable given observations of R_m, the return to all risky assets. This is clearly not possible, and we must use a proxy for R_m as discussed previously.

Going to the APT derivation we see that in the generating assumption

$$R_i = E(R_i) + b_i\delta + e_i \ ,$$

we need to assume that $\delta = R_m^v - E(R_m^v)$, where R_m^v is the volume weighted CRSP market return -- or for that matter any observable return, and this suffices to give us the model $R_i = (1 - b_i)E_0 + b_iR_m^v + e_i$. This model is estimable and the beta corresponds to the true cov/var of the generating model. For the purposes of our study, the assumption that δ

is an observable variable will ostensibly be the justification for the model estimation we use, however, we shall provide a brief analysis now of the consequences of δ not equaling $R_m^v - E(R_m^v)$, or equivalently of what happens when CAPM is measured with a proxy.

The CAPM (the following argument for APT is virtually identical) yields equation (ii) when (i) is additionally assumed. R_m is not observable, but we note that R_m^v can be expressed as in (ii) by

$$\text{(iii)} \quad R_m^v = (1 - b_v)R_f + b_v R_m + e_v$$

By solving (iii) for R_m in terms of R_m^v, R_f, e_v, and b_v, and substituting this into (ii) yields

$$\text{(iv)} \quad R_i = (1 - (b_i/b_v))R_f + (b_i/b_v)R_m^v + (e_i - (b_i/b_v)e_v)$$

Our primary concern is with the instability of b_i. We can see that its' behavior will directly influence the stability of the estimated beta in (iv), and even though the correlation in the error term with R_m^v will cause inconsistency in the estimation, there is no reason for it to mask instability. Our own belief is that R_m^v is closely correlated with R_m and that e_v is small enough so that estimation with (iv) does not guide us too seriously off track. It is also interesting to note that the "fair game" assumption (i) used in CAPM to convert the expectations form of the model into the "observations" form (ii) is a specific example of the type of generating assumption one would make in using the APT. It would seem only natural then to rely on APT for the theoretical justification of the "observations" form of the model.

Equation (ii) may also be written

(v) $R_i = R_f + b_i(R_m - R_f) + e_i$ or

(vi) $R_i - R_f = b_i(R_m - R_f) + e_i$

This last form of the model is often referred to as the equilibrium constrained form. For practical and expositional purposes we will use this form of the model throughout the remainder of the dissertation, keeping in mind the fact that it is derivable from either CAPM or APT (with $E_o = R_f$). In the empirical work which will follow, we will use the market yield on three month treasury bills as an estimate for R_f when conducting estimation with monthly data. We should also point out that we additionally carried out much of the work with the model (v) and the unconstrained form of the model

(vii) $R_i = a_i + b_iR_m + e_i$

With regard to inference concerning beta stability we found no difference in the results using any of the above mentioned models. We emphasize the fact that within the CAPM or APT framework we are justified in using the equilibrium constrained form of the model, and this has the additional benefit over the unconstrained form of having only <u>one</u> parameter (b_i, as opposed to a_i and b_i) to which responsibility can be placed for inducing statistics indicating potential instability. The unconstrained model (vii) is more commonly referred to as the market model, and was the precursor to CAPM. It was suggested originally as a model which captured the great commonality in movement between stock returns for firms and the market as a whole. One could argue, however, that Ross' generating assumption (such as (i)) is in fact a better representation of this commonality.

II

PROPOSED STATISTICS TO TEST FOR PARAMETER INSTABILITY

Section 2.1 Overview

Under the null hypothesis H_0 of parameter stability, OLS provides the most efficient method of estimation. This is due to the fact that the matrix of explanatory variables (a vector of 1's and the vector of market returns) is identical for all firms, and therefore pooling data and applying Zellner's Seemingly Unrelated Regressions (SUR) reduces to OLS estimation. Under H_0,SUR is the only way to increase efficiency by pooling data (with the single factor model). It would therefore seem plausible to base our analysis of departure from parameter stability upon an analysis of the OLS residuals. Unfortunately, these residuals will be correlated over time, and so statistics based upon them will not readily yield manageable distributions. We may solve this problem by producing unbiased transformations of the OLS residuals into sets of uncorrelated residuals. Because we are working in the time domain, it would seem only natural to require that these transformations preserve the order of statistics formed, as this will aid us in capturing time effects.

With these constraints it can be shown that there exists a unique transformation meeting our requirements.

This transformation produces the so-called recursive residuals of Brown, Durbin, and Evans (BDE- (2)). They are a member of a general class of residuals known as LUS residuals (Linear, Unbiased, Scalar covariance matrix), which are discussed in Theil (13) as a preface to his development of BLUS residuals (Best LUS). LUS residuals have recently been shown to be related to each other by orthogonal transformations, and to be equivalent to Linear Invariant (LI) residuals. The invariance refers to the property that $w'w = e'e$, where w is a vector of LUS residuals, and e is the corresponding vector of least squares residuals upon which they are based. This equivalence, along with other interesting properties of LUS residuals have been established by Godolphin and deTullio (4). Recursive residuals are the unique member of the LUS class that have the time ordered properties we desire, and may be shown to be equal to the one step ahead forecast error (standardized so as to have common variance). Given the regression model $Y = X\beta + U$ under classical assumptions, we define

$$w_r = \frac{y_r - x_r b_{r-1}}{(1+x_r(X'_{r-1}X_{r-1})^{-1}x'_r)^{1/2}} = \frac{y_r - x_r(X'_{r-1}X_{r-1})^{-1}x'_{r-1}y_{r-1}}{(1+x_r(X'_{r-1}X_{r-1})^{-1}x'_r)^{1/2}}$$

$r = k+1, \ldots, T$ and where;

$X'_{r-1} = (x_1, \ldots, x_{r-1})$

b_{r-1} = O.L.S. estimator of β based on the first $r-1$ observations

k = number of independent variables in the model

The w_r are obviously normal mean zero and with variance σ^2 (say). The numerator is the L.S. predictor with variance $\sigma^2(1+x_r(X'_{r-1}X_{r-1})^{-1}x'_r)$. Additionally we have $E(w_r w_s) = 0$ (a straight forward exercise in expanding terms) which suffices to establish independence in normally distributed (mean zero) random variables. These residuals are easily computed(simple recursive formulae exist for updating both b_j and $(X'_jX_j)^{-1}$).

Section 2.2 CUSUM, CUSUMSQUARE, and the Quandt Likelihood Ratios (QLR)

One of the first tests to use recursive residuals in testing for non-stable parameters was the cusum test developed by Brown, Durbin, and Evans (BDE). Beside providing a test in the statistical sense, this approach has the added appeal of providing a visual aid to detecting model instability.

BDE (2) construct scaled, running sums of recursive residuals called CUSUMS;

$$W_r = \frac{1}{\hat{\sigma}} \sum_{k+1}^{r} w_j, \quad r = k+1, \ldots, T$$

which are examined under the null hypothesis H_0 of stable coefficients, and where $\hat{\sigma}$ is an estimate of the common standard deviation of the w_j. BDE originally used

$$[\sum_j w_j^2/(T-k)]^{1/2}$$

as their estimate of $\hat{\sigma}$, but in the comments to (2), Harvey pointed out that the alternative

$$\hat{\sigma}^* = [\sum_j (w_j - \bar{w})^2/(T-k-1)]^{1/2}$$

would improve the procedure, as the cusum will tend to be larger in absolute value under the alternative hypothesis. An added advantage of this new $\hat{\sigma}^*$ is the fact that

$$W_T \hat{\sigma}^{*-1}/(T-k)$$

has a t-distribution under H_0 (see Harvey and Collier (5)). The $\{W_r\}$ form a sequence of asymptotically normal variables such that $E(W_r) = 0$, $V(W_r) = r - k$ and $Cov(W_r, W_s) = \min(r,s) - k$, to a good approximation. By approximating W_r with a continuous Gaussian process, BDE develop "confidence bands" around plots of W_r for $r = k + 1, \ldots, T$. Anderson (2) points out that cusums will yield a slightly conservative test, due to the continuous approximation. We reject H_0 if the plot of cusums "strays" outside the bands. The behavior of the plot may reveal information regarding coefficient movement independent of the testing procedure. BDE emphasize that the function of the "band lines" is to provide a yardstick against which to assess the observed behavior of the plot. This is to be especially emphasized since the current software packages offering CUSUM (Troll (14) and a package built by BDE called TIMVAR) compute $\hat{\sigma}$ by the less powerful relationship suggested by BDE originally. In our own work we have rarely found CUSUM able to reject stability statistically, however the plot behavior often leads one to suspect its presence. Garbade (3) ran simulations of instable models using the original BDE formulation for $\hat{\sigma}$ and also found CUSUM unable to cross one or five percent confidence bands when instability of varying degrees was present.

When coefficient instability takes the form of a switch from one stable regime to another, it is easy to see how the systematic nature of change will cause the cusums W_r to deviate away from zero (in one direction) until they cross a certain confidence band. On the other hand, a haphazard departure from constancy may not permit the cusums to "build" away from zero, but may simply cause fluctuations. To cope with this problem, BDE suggest plotting and developing a test on CUSUM SQUARES;

$$s_r = \sum_{j=k+1}^{r} w_j^2 \Big/ \sum_{j=k+1}^{T} w_j^2 = \frac{S_r}{S_T} \qquad r = k+1, \ldots T$$

Under H_0, s_r has a beta distribution with mean $(r-k)/(T-k) = \mu_r$ (see Rao (10)). A plot of the means μ_r forms a line with slope $1/(T-k)$, and BDE develop a technique for placing parallel lines about this plot so that the probability of the sample path crossing one or both lines is α, a specified significance level. Our own experience with CUSUMSQUARE as a statistical test is that it performs well relative to CUSUM, in that it rejects stability when the Quandt Likelihood Ratios (described in further detail below) indicate this is likely, and do not reject when QLR indicates no instability.

Garbade corroborates this observation in his simulation work, which often finds CUSUMSQUARE quite powerful for the particular models he examines (simple regression where the parameter is (i) a random walk with zero drift, (ii) a discrete jump, and (iii) a Stable Markov process).

Quandt (9) introduced a maximum likelihood procedure for finding an abrupt shift from one stable parameter regime to another. Under the assumption of normal errors in a regression model, the likelihood under dual regimes takes on a simple form, and the likelihood ratio $\lambda_{t*} = L(\hat{w})/L(\hat{\Omega})$, where $L(\hat{w})$ is the likelihood under the assumption of one regime, and $L(\hat{\Omega})$ is the maximum likelihood achieved by partitioning the data time-wise as two regimes over the entire estimable range, reduces nicely to

$$\lambda_{t*} = \hat{\sigma}_1^{t*} \cdot \hat{\sigma}_2^{T-t*} / \hat{\sigma}^T$$

Here T is the number of time units, t* the time at which an optimal partition occurs, $\hat{\sigma}_i$ the estimated standard error of regime i, and $\hat{\sigma}$ the estimated standard error of the regression over all the data. While this procedure is feasible for spotting the location of a possible shift (it can easily be implemented on a computer for even large data sets), it does not offer a means for statistically corroborating the existence of a shift. It was originally thought that functions of λ (particularly $-2\log\lambda$) would provide known distributions (possibly asymptotic). Unfortunately the discrete time frame we are working in lacks properties necessary to derive feasible statistics. The Quandt procedure survives primarily as a tool to aid in spotting shift location, although plots of λ_t may be used to "shed light" on the stability of the regression, and to indicate whether changes have occurred as an abrupt transition or gradually. The implementation of this technique used in following sections is based on plots of $\log_{10}\lambda$. Because λ takes on values between zero and one, we see from inspection of λ_{t*} above that the minimum of plot values for $\log_{10}\lambda_t$ will indicate the optional point of partition of the data. Although QLR is designed to test against the specific alternative of two regime switching, we have found the plots useful as a heuristic tool when more than one shift occurs. While the global minimum of the plot still serves to point to the optimal partition of the data if a single partition of the data is desired, other "local" minima may point to other less severe shifts in beta. We have found that the QLR plot maintains its basic form and behavior when only a segment of the total data available is used -- versus how that portion of time plots when the full data set is employed. Another way to view this is to relate the likelihood ratio to the CUSUMSQUARE statistics. In order to do so we shall have to introduce some notation and describe briefly another version of CUSUMSQUARE that can be implemented.

If we desired, CUSUM or CUSUMSQUARE could be obtained

Similarly, the term

$$\left(\frac{ess_2}{ess}\right)^{(T-t)/2} = (S^B_{T-t})^{(T-t)/2}$$

We may therefore write

$$\lambda_t = \left(\frac{ess_1}{ess}\right)^{t/2} \left(\frac{ess_2}{ess}\right)^{(T-t)/2} \cdot \gamma_t$$

$$= (S^F_t)^{t/2} (S^B_{T-t})^{(T-t)/2} \cdot \gamma_t$$

In the above, we have used the fact that

$$\hat{\sigma}_i = \left(\frac{ess_i}{n}\right)^{1/2} ,$$

where n is the number of data points used in the estimation.

Given this valuation for λ_t, it does not seem implausible that the QLR may be robust to a situation where multiple switches occur, or for that matter where any alternative to beta stability is present. The CUSUMSQUARE statistics S^F_t and S^B_{T-t} are sensitive to any alternative non-stable parameter behavior. If for example, there were a switch in beta near the beginning of a series at time t_1, and another toward the end at t_2, then the two statistics

$$\lambda_{t_i} = (S^F_{t_i})^{t_i/2} (S^B_{T-t_i})^{(T-t_i)/2} \gamma_t \qquad i = 1, 2$$

and plotted by running the analysis backwards through time. In this case we still have the denominator of the CUSUMSQUARE statistic S_T the same as for the forward analysis since

$$S_T = \sum_{j=k+1}^{T} w_j^2 = ESS$$

Let us now denote the backward CUSUMSQUARE statistics by S_r^B, and the forward statistic by S_r^F. We can now relate these statistics to the QLR as follows:

$$\lambda_t = \frac{\hat{\sigma}_1^t \cdot \hat{\sigma}_2^{T-t}}{\hat{\sigma}^T}$$

$$= \frac{(ess_1)^{t/2}(ess_2)^{(T-t)/2}}{(ess)^{T/2}} \quad \frac{T^{T/2}}{(t^{t/2})(T-t)^{(T-t)/2}}$$

$$= \frac{(ess_1)^{t/2}(ess_2)^{(T-t)/2}}{(ess)^{t/2}(ess)^{(T-t)/2}} \quad \gamma_t$$

We now note that the term

$$\left(\frac{ess_1}{ess}\right)^{t/2} = \left(\frac{\sum_{j=k+1}^{t} w_j^2}{\sum_{j=k+1}^{T} w_j^2}\right)^{t/2}$$

$$= \left(\frac{S_t}{S_T}\right)^{t/2} = (S_t^F)^{t/2}$$

may translate in the QLR plot of $\log\lambda_t$ into "low" points for $\log\lambda_{t_1}$ and $\log\lambda_{t_2}$ since $S^F_{t_1}$ and $S^B_{T-t_2}$ should deviate from their expected behavior under stable regimes, and in fact be smaller than expected.

III

EXAMPLES OF BETA INSTABILITY IN THE ELECTRIC UTILITY INDUSTRY

Section 3.1 Model Used in the Analysis

We present below an examination of the stability of beta in the CAPM for a particular firm (Consolidated Edison of New York -- Con Ed) for which instability has been suspected, and then for an equally weighted portfolio of ninety electrics. Because the software employed (TROLL) is unable to carry out calculation on a model with a single regressor, we employed the following version of the constrained CAPM (as discussed in Section I);

$$R_i - R_f = a + b_i(R_m - R_f)$$

as opposed to

$$R_i - R_f = b_i(R_m - R_f)$$

In both of the examples below, the parameter "a" in the model was estimated as insignificantly different from zero. The volume weighted index from the CRSP data base (see below) was used for R_m, and the market yield on three month treasury bills was employed for R_f.

Section 3.2: Parameter Instability Tests for Consolidated Edison

We present on exhibits 3.1-3.3 results of the Quandt Likelihood Ratios (QLR), CUSUMSQUARE (5%), and CUSUM (5%) tests for parameter stability in the model

$$R_{ConEd} - R_f = a + b_{ConEd}(R_m - R_f)$$

OLS estimates of a and b_{ConEd} and their t-statistics are:

	EST COE F	t-STAT (d.f. =82)
a	0.008	0.801
b	1.021	4.726

The period of estimation was from January, 1971 until December, 1977 using monthly observations obtained from the CRSP data bank (Center for Research on Security Prices, University of Chicago). The period investigated contains several events that were felt to have impacted on investors' assessment of the riskiness of Con Ed's stock. On October 18, 1973 the announcement concerning an Arab oil embargo appeared, and on April 18, 1974 Con Ed announced that for the first time in ninety-four years it would not pay out a dividend on its common stock. We have circled the QLR values corresponding to October and November of 1973 (monthly return values are measured at the end of the month), and also for March and April 1974. While a possible link to the oil embargo is indicated, it is the extreme change in value from the March to April QLR points that appear most noteworthy. This change may possibly be attributable to the Con Ed dividend decision, but not to the Oil Embargo (as it occurred roughly five months before). Behavior of the plot later in time also seems to indicate instability of a somewhat less severe nature.

CUSUMSQUARE clearly rejects stability and crosses both "confidence bands." The first "crossing" appears to correspond to the monotonically decreasing sequence of values found over the same time period in the QLR, and the second crossing (not as severe) to the instability suspected in the second portion of QLR. CUSUM does not reject stability, but as we mentioned in the previous section this is not unexpected. CUSUM is useful primarily as a visual aid. In this instance we see that it behaves in accordance with stable behavior until the circled value which corresponds to March, 1974. The evidence presented here is consistent with speculation that the dividend decision may have acted as a signal to investors concerning a change in the risk characteristics of Con Ed. It is not clear whether or not the oil embargo had much of an effect, at least when compared to that of the dividend decision.

Section 3.3 Tests On The Industry Portfolio

Results of the QLR, CUSCUMSQUARE (5%), and CUSUM (5%) are presented in exhibits 3.4-3.6 for the model

$$R_p - R_f = a + b_p(R_m - R_f)$$

where R_p is the vector of monthly time series observations for an equal weighted portfolio of electric utilities. The set of electric utilities consisted of all listed electrics on the CRSP tapes with continuous data from January 1971 until December 1977, and there were ninety such firms.

OLS estimates of a and b_p and their t-statistics are;

	EST COE F	t-STAT (d.f. = 82)
a	0.0016	0.407
b	0.7417	8.880

We have indicated on the QLR display the points corresponding to October 1973, April 1974, and June 1975. Impact of the oil embargo to the industry does not appear to exhibit itself through any noteworthy behavior on the QLR, and similarly with the Con Ed decision date. There was belief that Con Ed's dividend decision acted as a signal not only to Con Ed's stockholders, but also to investors in the industry as a whole. Relative to the monthly time framework it appears that there was little effect on the industry by the Con Ed decision. The data clearly indicates optimal partitioning around June, 1975. The economy was coming out of a recession at this time, but it is unclear what other events or what mechanism may have been responsible for this response. If in fact the cause of this potential instability (we must verify with CUSUMSQUARE to test the significance of it) was recession related, we may have some hope that a macroeconomic determinant or indicator of the economy (such as the prime rate) may serve to explain beta instability. We will examine this question further in a following paper.

CUSUMSQUARE (5%) rejects stability and does so after an "erratic jump" near the middle of the plot, and slight movement toward the lower critical band at about the one-third mark in the plot. CUSUM exhibits a drifting pattern from the half-way point on, and by the end of the plot reaches values of fifteen (with twenty-five the critical level, and zero the expected value under the null hypothesis). Our conclusion is that the industry beta exhibits instability primarily in the second half of the time period investigated, and owing to the erratic behavior of the QLR in this period the beta movement most likely involves multiple regimes.

3.4 The primary implication of this research is the clear rejection of the traditional use of the CAPM for use in estimating beta in the electric utility industry. Furthermore, the types of tests employed in this study can provide us with a "picture" of the nature and severity of an instable beta. In the case of many of the individual firms, examination of the Quandt Likelihood Ratios indicate only a few (or even single) switches in beta, and a simple partitioning of the data may yield stable regimes. For example, consider Exhibits 3.7 and 3.8 of the QLR and Cumsumsquare displays for Iowa-Illinois Gas and Electric Company (1/71 till 12/77). After the secondary minimum (circled) it would appear that the plot does not exhibit any strong indications of instability. If the use of the thirty-five or so data points (2/75 till 12/77, or two years and ten months of data) were acceptable to a regulatory commission, then it may be that beta could be estimated from this data if it could be established that it was stable. This is easy enough to check, and Exhibits 3.9 and 3.10 (of QLR and Cumsquare) corroborate what the full data set "hinted" at. The QLR is relatively smooth, and cusumsquare does not reject the null hypothesis of stability (as with all Cumsquare tests we use 5 percent significance bands). Examination of stability tests for all of the individual firms comprising the sample indicates a substantial number of firms with instability problems similar to Iowa-Illinois'. A listing of the firms included in the study is provided in the appendix.

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EXHIBITS AND APPENDIX

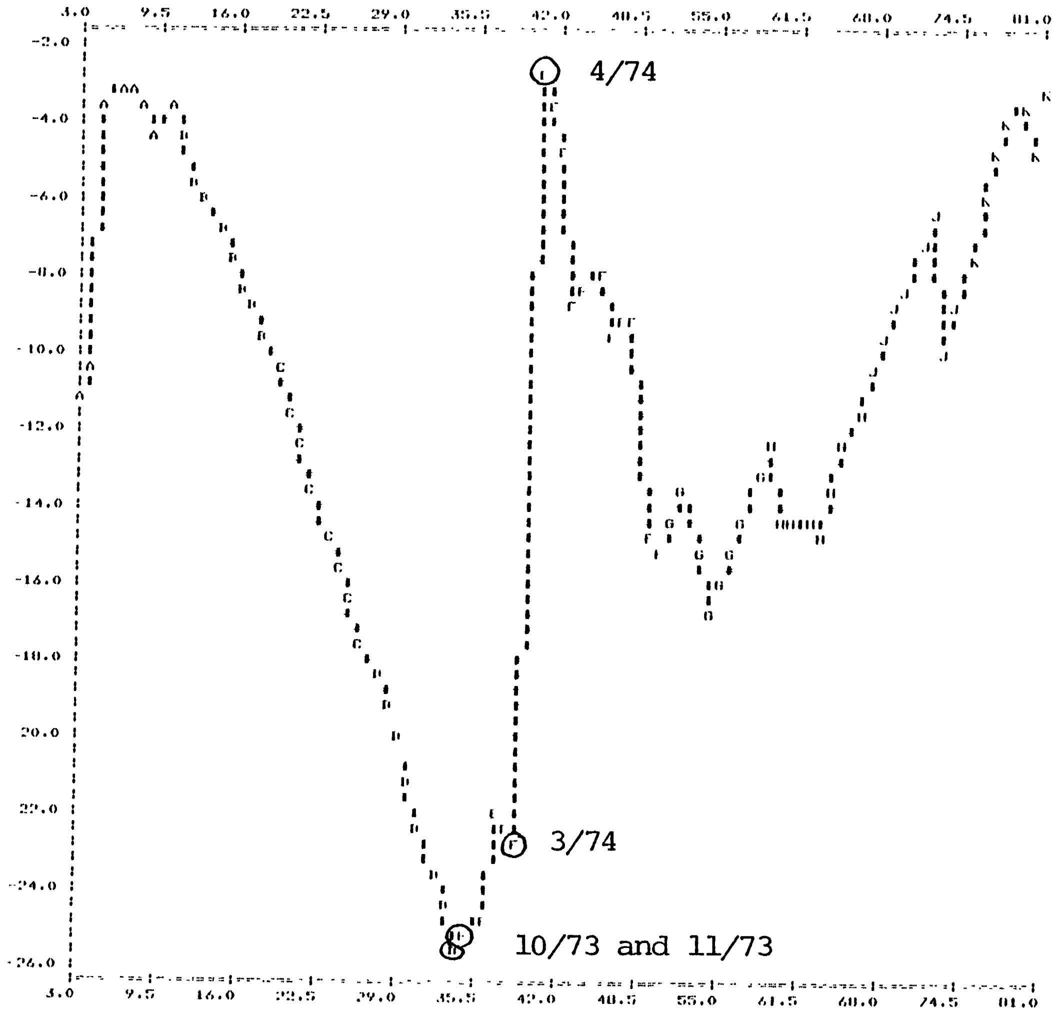

Exhibit 3.1 Quandt Likelihood Ratios (Con Ed)

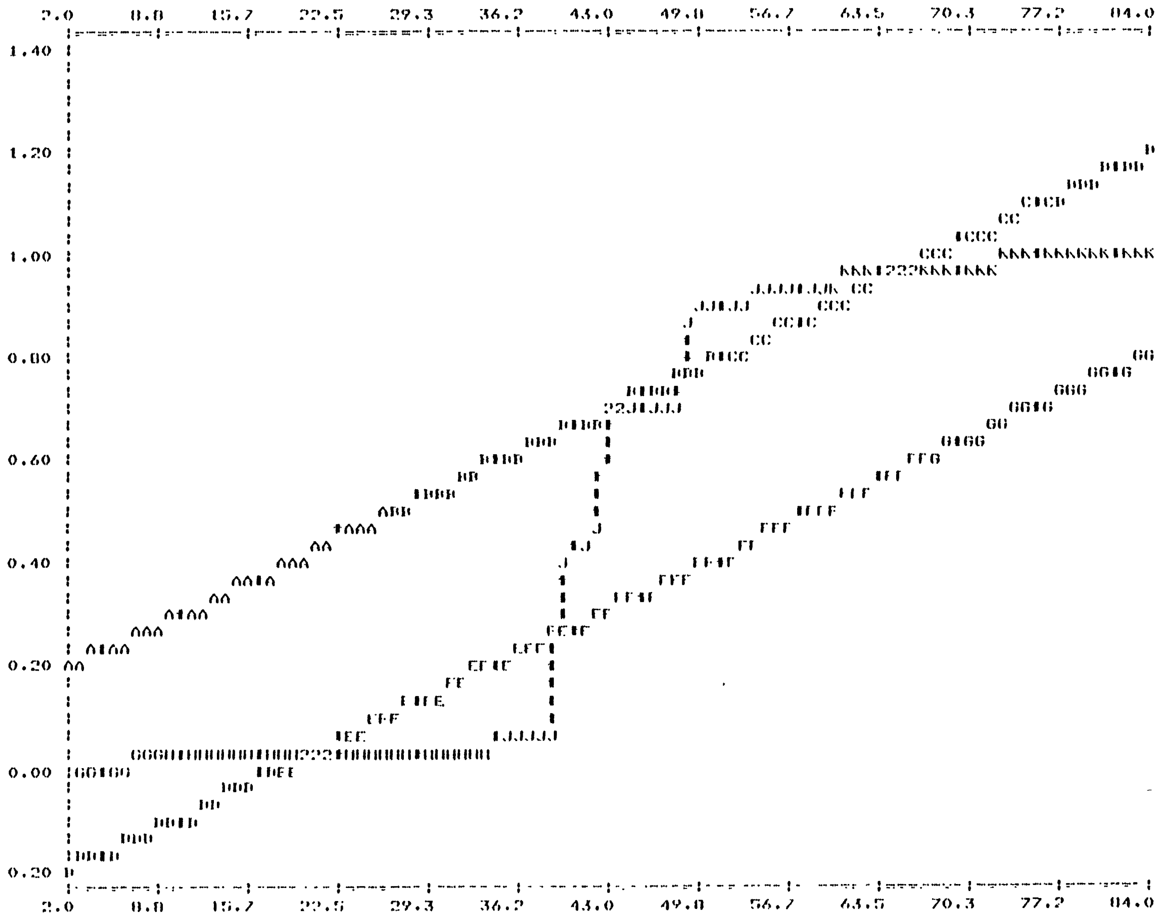

Exhibit 3.2 Cusumsquare Display for Con Ed

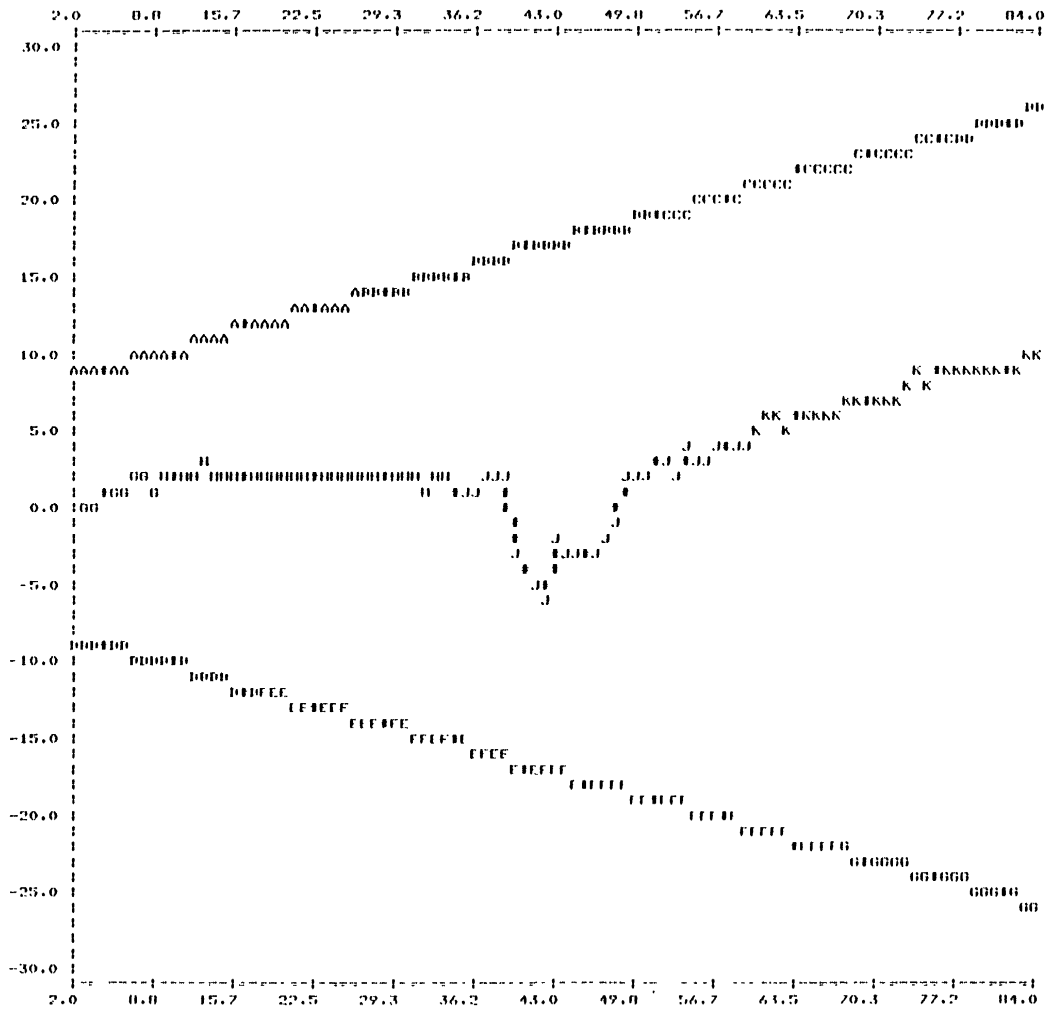

Exhibit 3.3 Cusum Display for Con Ed

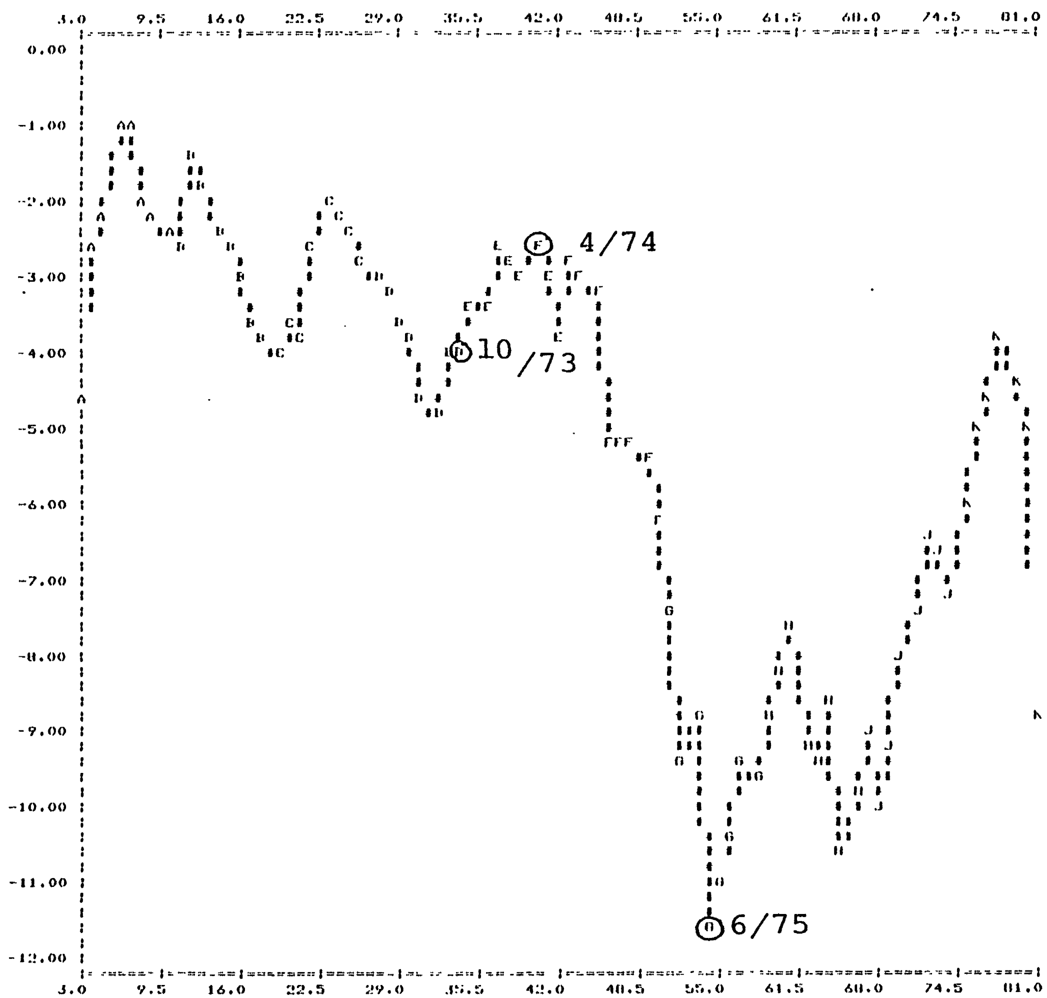

Exhibit 3.4 Quandt Likelihood Ratios (Electric Portfolio)

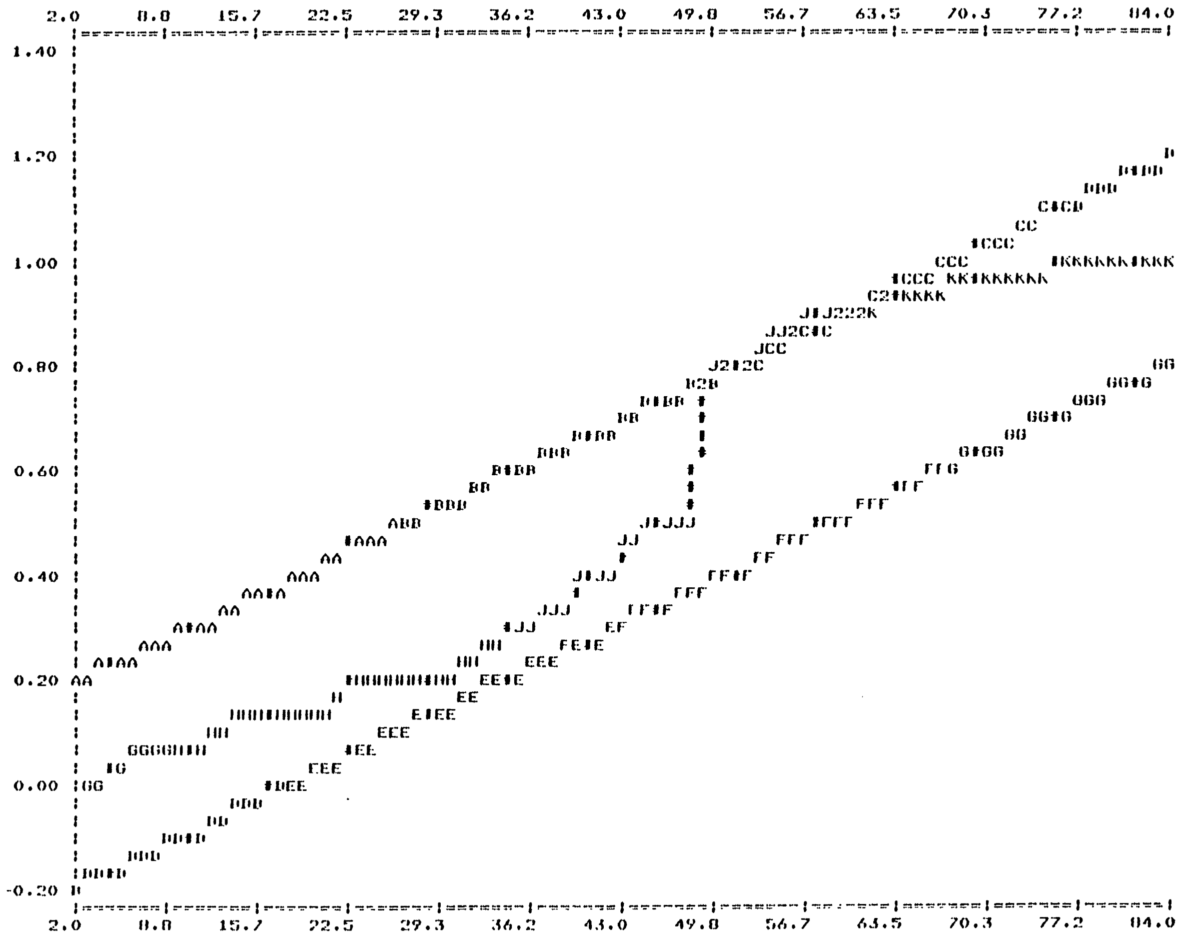

Exhibit 3.5 Cusumsquare Display for Electric Portfolio

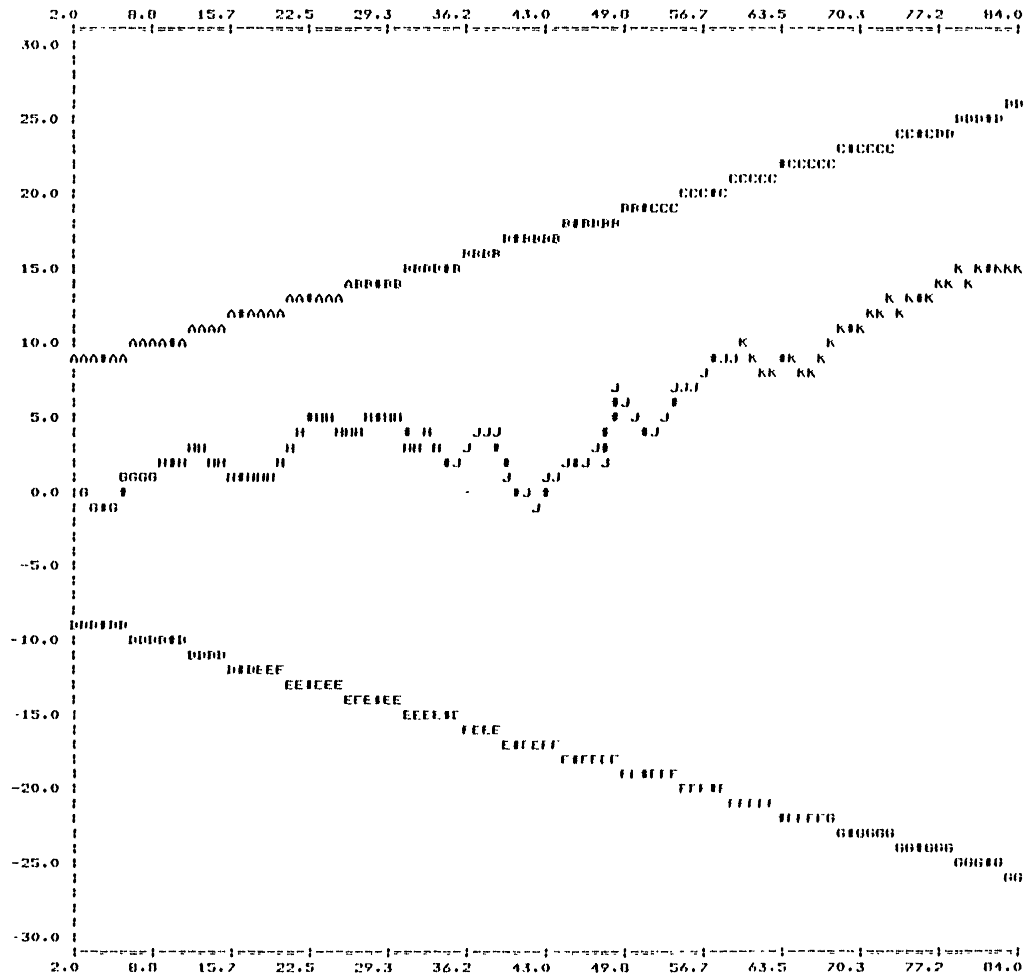

Exhibit 3.6 Cusum Display for Electric Portfolio

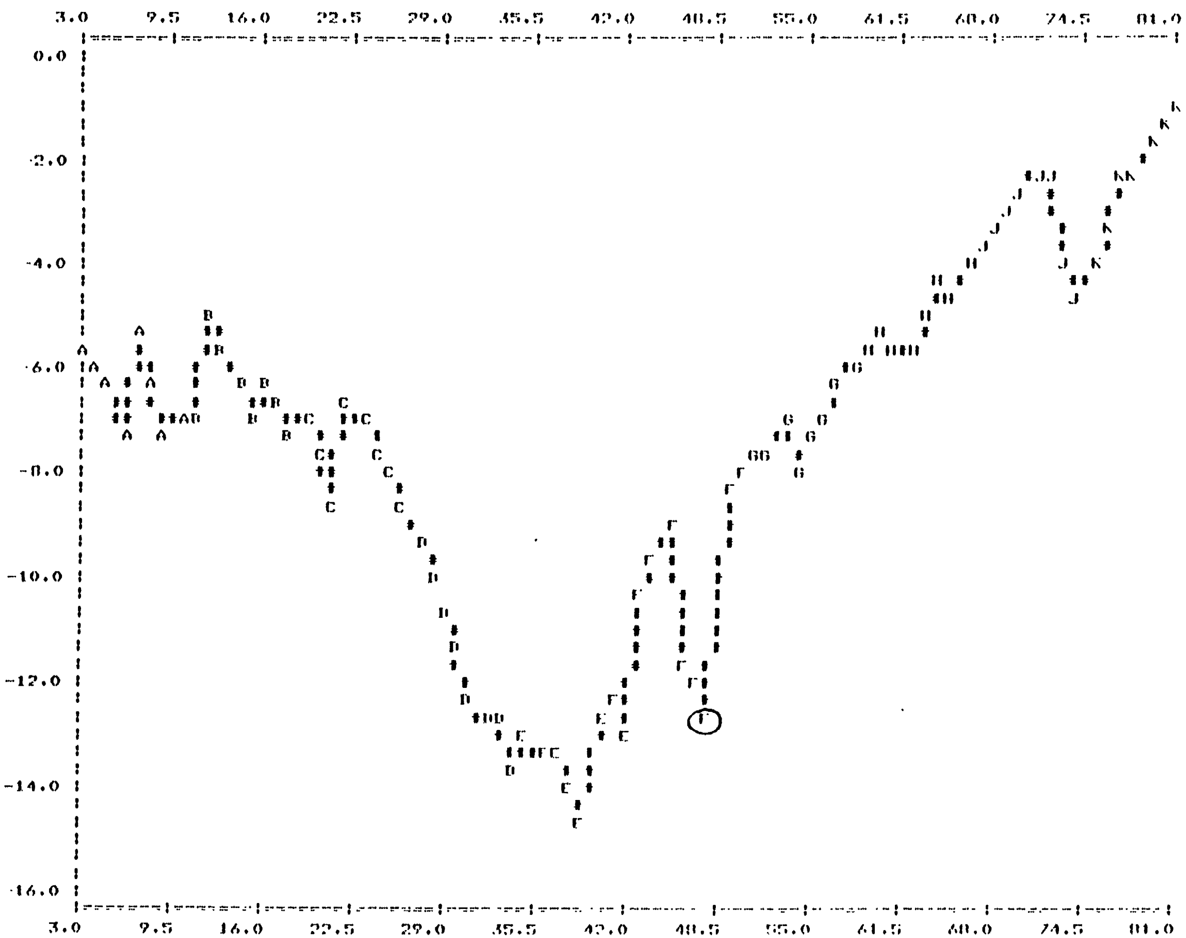

Exhibit 3.7 Quandt Likelihood Ratios (Iowa-Illinois Gas and Electric)

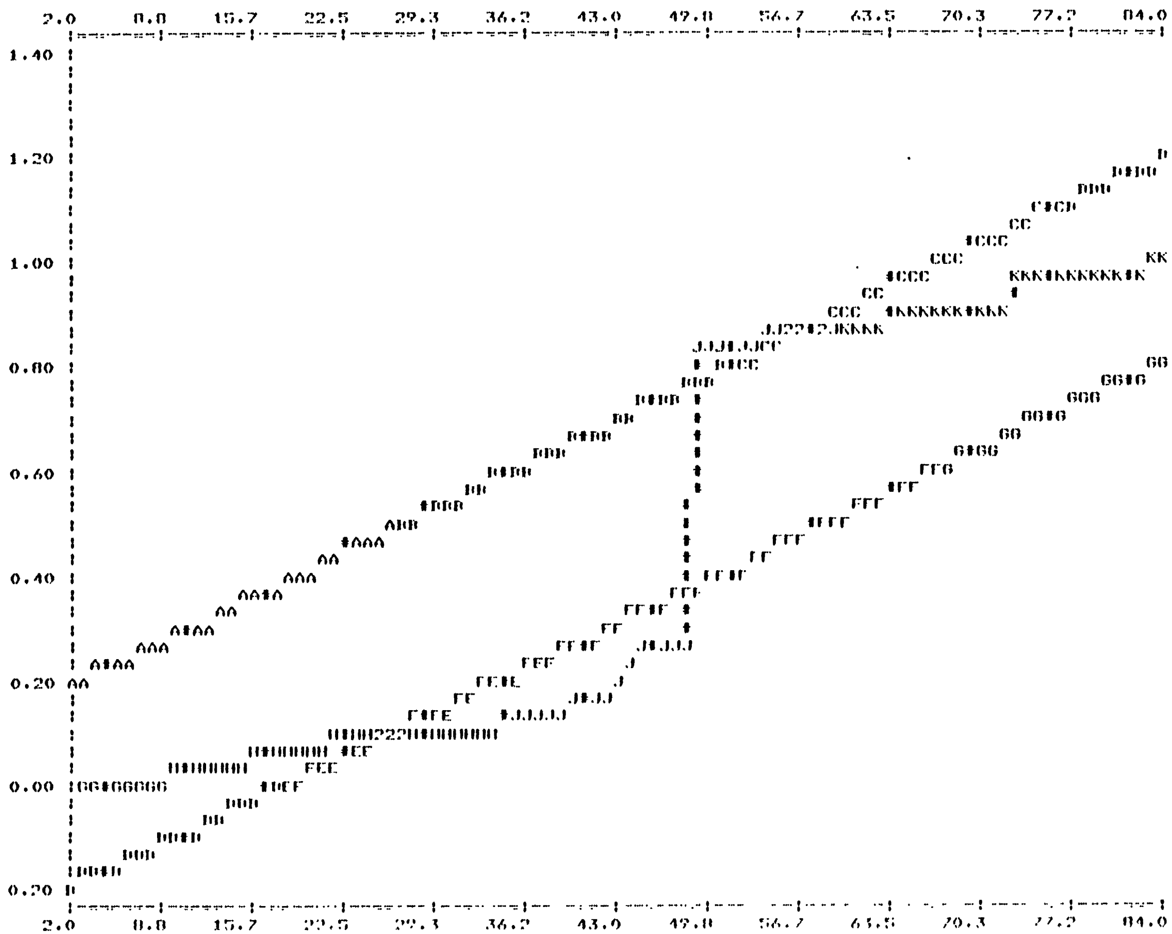

Exhibit 3.8 Cusumsquare Display for Iowa-Illinois Gas and Electric

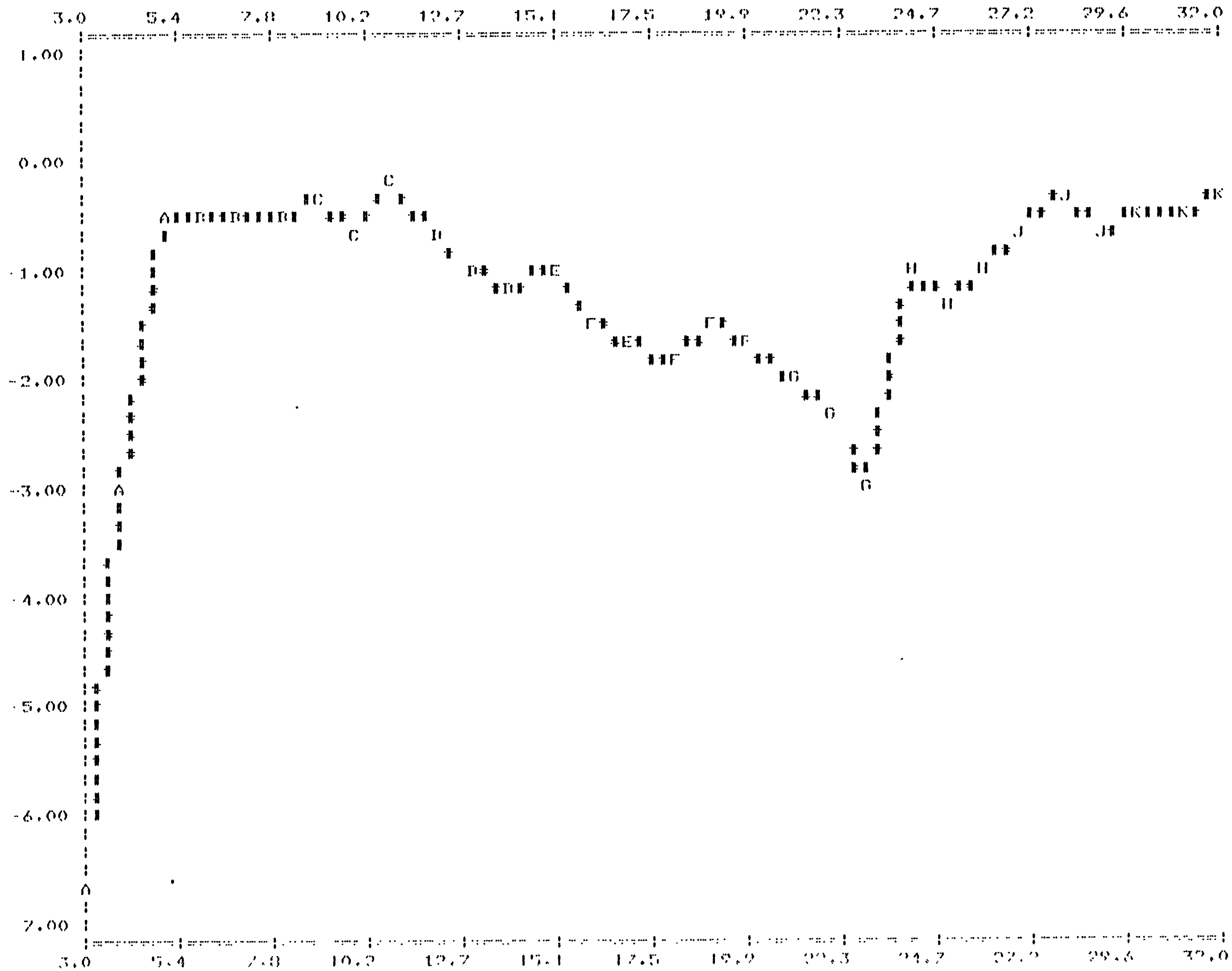

Exhibit 3.9 Quandt Likelihood Ratios (Iowa-Illinois with beta modeled)

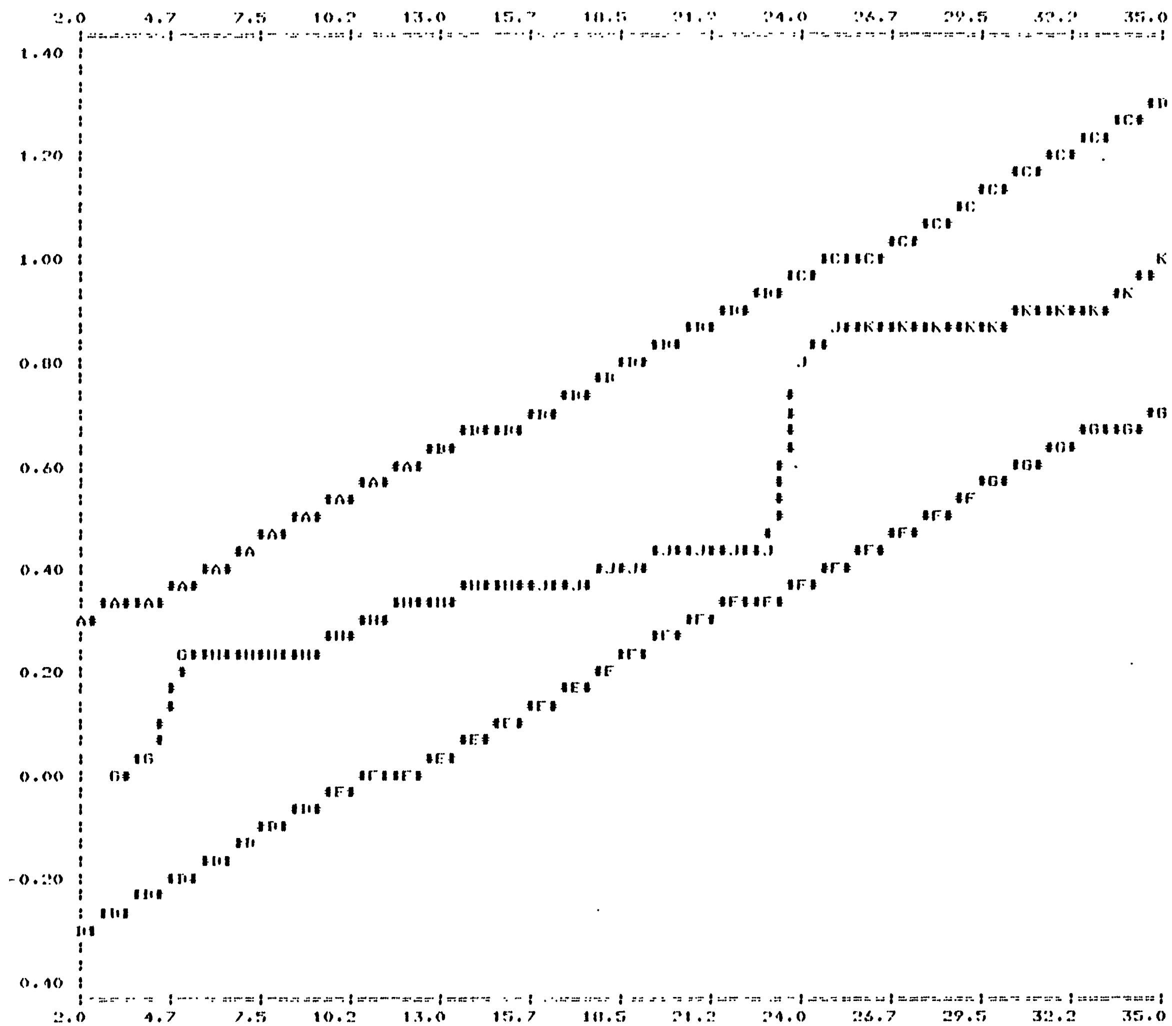

Exhibit 3.10 Cusumsquare Display for Iowa-Illinois with beta modeled

APPENDIX

1. ALLEGHENY PWR SYS INC
2. AMERICAN ELEC PWR INC
3. ARIZONA PUB SVC CO
4. BALTIMORE GAS & ELEC CO
5. BOSTON EDISON CO
6. CAROLINA PWR & LT CO
7. CENTRAL & SOUTH WEST CORP
8. CENTRAL HUDSON GAS & ELEC CORP
9. CENTRAL ILL LT CO
10. CENTRAL ILL PUB SVC CO
11. CENTRAL LA ELEC INC
12. CENTRAL ME PWR CO
13. CINCINNATI GAS & ELEC CO
14. CLEVELAND ELEC ILLUM CO
15. COLUMBUS & SOUTHN OHIO ELEC CO
16. COMMONWEALTH EDISON CO
17. CONSOLIDATED EDISON CO N Y INC
18. CONSUMERS PWR CO
19. DAYTON PWR & LT CO
20. DELMARVA PWR & LT CO
21. DETROIT EDISON CO
22. DUKE PWR CO
23. DUQUESNE LT CO
24. EASTERN UTILS ASSOC
25. EMPIRE DIST ELEC CO
26. FLORIDA PWR & LT CO
27. FLORIDA PWR CORP
28. GENERAL PUB UTILS CORP
29. GULF STS UTILS CO
30. HAWAIIAN ELEC INC
31. HOUSTON INDS INC
32. IDAHO PWR CO
33. ILLINOIS PWR CO
34. INDIANAPOLIS PWR & L, CO
35. INTERSTATE PWR CO
36. IOWA ELEC LT & PWR CO
37. IOWA ILL GAS & ELEC CO
38. IOWA PWR & LT CO
39. IOWA PUB SVC CO
40. KANSAS CITY PWR & LT CO
41. KANSAS GAS & ELEC CO
42. KANSAS PWR & LT CO

43. KENTUCKY UTILS CO
44. LONG ISLAND LTG CO
45. LOUISVILLE GAS & ELEC CO
46. MIDDLE SOUTH UTILS INC
47. MINNESOTA PWR & LT CO
48. MISSOURI PUB SVC CO
49. MONTANA DAKOTA UTILS CO
50. MONTANA PWR CO
51. NEVADA PWR CO
52. NEW ENGLAND ELEC SYS
53. NEW YORK ST ELEC & GAS CORP
54. NIAGARA MOHAWK PWR CORP
55. NORTHEAST UTILS
56. NORTHERN IND PUB SVC CO
57. NORTHERN STS PWR CO MINN
58. OHIO EDISON CO
59. OKLAHOMA GAS & ELEC CO
60. ORANGE & ROCKLAND UTILS INC
61. PACIFIC GAS & ELEC CO
62. PACIFIC PWR & LT CO
63. PENNSYLVANIA PWR & LT CO
64. PHILADELPHIA ELEC CO
65. PORTLAND GEN ELEC CO
66. POTOMAC ELEC PWR CO
67. PUBLIC SVC CO COLO
68. PUBLIC SVC CO IND INC
69. PUBLIC SVC ELEC & GAS CO
70. PUGET SOUND PWR & LT CO
71. ROCHESTER GAS & ELEC CORP
72. ST JOSEPH LT & PWR CO
73. SAN DIEGO GAS & ELEC CO
74. SAVANNAH ELEC & PWR CO
75. SIERRA PAC PWR CO
76. SOUTH CAROLINA ELEC & GAS CO
77. SOUTHERN CALIF EDISON CO
78. SOUTHERN CO
79. SOUTHERN IND GAS & ELEC CO
80. SOUTHWESTERN PUB SVC CO
81. TAMPA ELEC CO
82. TEXAS UTILS CO
83. TOLEDO EDISON CO
84. TUCSON GAS & ELEC CO
85. UNION ELEC CO
86. UTAH PWR & LT CO
87. VIRGINIA ELEC & PWR CO
88. WASHINGTON WTR PWR CO
89. WISCONSIN ELEC PWR CO
90. WISCONSIN PUB SVC CORP