EVENT STUDY METHODOLOGY: A NEW AND STOCHASTICALLY FLEXIBLE APPROACH

by

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1. Introduction

A number of studies have documented that the classical event study methodology exhibits a bias toward detecting "effects," irrespective of whether such effects actually exist.[1] This paper addresses this bias by presenting a new methodology that explicitly incorporates stochastic behaviors of the market that are documented to exist and which are assumed away by the classical event study methodology. Specifically, our methodology involves utilizing a market model that incorporates *ARCH* (autoregressive conditional heterskedastic) effects, includes time-varying systematic risk parameter (beta), and time-varying conditional variance. Further, a portmanteau test statistic based on cumulative sums (*CUSUM*) of standardized one-step-ahead errors is developed. Another important advantage of our proposed approach is that it also addresses issues affecting the statistical power of the classical event study methodology, namely concerns about the appropriate width of the event window, as well as the exact timing of the event.

Besides providing a new method of event analysis, we use this method to reanalyze the effects of a significant regulatory event (specifically, the passage of California's Proposition 103) which had previously been investigated using classical event study techniques. We show, using our new methodology, that once the known market behaviors are explicitly modeled, exactly the opposite conclusion about the effects of this particular event results.

This paper proposes a dynamic model for simultaneously incorporating time-varying systematic risk (beta) and conditional heteroskedasticity in the calculation of returns during the

[1] For example, see the papers by Boehmer, Musumei and Poulsen (1991), Brown and Warner (1985), and Frankfurter and McGoun (1993).

estimation period.[2] Excess returns are defined as the standardized one-step-ahead forecast errors (instead of residuals as used in the classical event study methodology). The one-step-ahead forecast errors are calculated using the Kalman filter technique. A portmanteau test is developed to test whether the cumulative abnormal returns (*CAR*) are significantly different from zero. This test, based upon cumulative sum (*CUSUM*) techniques, allows a longer event window without the need to pinpoint the timing of the event. Accordingly, it would not lose the power when the exact event date is uncertain (as does the classical event study methodology).[3] In addition, a graph of the *CAR* can provide a rough indication concerning the point at which the market began to react to the event. This is an important contribution in cases such as Proposition 103, where information gradually diffuses into the market. The philosophy behind our work is similar to the problem in the statistics literature of detecting points of change. We do not directly endogenize the type or time of change into the model, but instead infer a change when the statistic exceeds a threshold level.

The paper is organized as follows. In the next section, the methodology is presented. We define the standardized forecast errors on which the test statistic is based, and present several simulation examples. In the third section of the paper, we apply our proposed model to an

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[2] Boehmer, Musumei and Poulsen (1991) simulate an event with stochastic effects. They conclude that when an event causes even minor increases in variance, the most commonly-used methods reject the null hypothesis of zero average abnormal return too frequently; i.e., find an "effect" too often.

[3] As a result of their tests of event study methodology statistical power, Brown and Warner (1980) emphasize the importance of carefully defining event dates due to the possible adverse power effects of incorrectly defined event dates. The more days one must include in the event window (because of inability to pinpoint an event date) the lower the power of the classical event study methodology. Most of the studies define the event day as the day on which the event occurs (e.g., the day of a stock split or merger). This identification may obscure the issue of defining “occurrence”. For instance, Mandelker (1974) used the date of a merger and found no significant evidence of shareholder return effects. However, when Asquith *et al.* (1983) used the date on which the intent to merge was announced, they found significant ARs and cumulative ARs. For the event study considered here, we obtain similar results. The market reacted to an election result, not on the event (election) day, but rather eight days prior to the election.

examination of the effect of the passage of a California regulatory initiative, Proposition 103, on the stock values of insurance companies. This particular event has previously been analyzed in a number of previous studies that employ the classical event study methodology, so it provides an excellent case study for our methodology. The fourth section concludes the paper with a brief summary and conclusions.

2. Methodology

Excess returns are the mathematical difference between observed returns and the normal or expected returns based upon some model of the return generating process. The excess returns are also known by a variety of other names, including abnormal returns, excess returns, prediction errors, and average residuals. We propose a time-series regression with a Generalized Autoregressive Conditionally Heteroskedastic (*GARCH*) effect market model. This takes into account certain important characteristics of market models for security prices, namely stochastic, time varying non-diversifiable risk β, and a time varying heteroskedastic error structure. The estimation, identification and diagnostic checking procedures for the proposed model are discussed subsequently. Our new event study methodology is then developed based on cumulative sums (*CUSUM*) of standardized one-step-ahead forecast errors (based upon the stochastic β and *GARCH* error market model) in order to detect the manner in which (and statistical significance of) a particular event affects the market.

2.1 Model Selection

Much of the event study literature is based on a market model relating the return on an individual asset to the return on a market index and an asset-specific constant. The basic market model can be written as

$$r_{it} = \alpha_i + \beta_i \cdot r_{mt} + e_{it}, \tag{1}$$

where r_{it} is the one-period return on asset i at time t, r_{mt} is the return on the market index at time t, and e_{it} is an uncorrelated error term with mean 0 and constant variance σ_e^2. For simplicity, we subsequently omit the index *i*. The parameters in this model are assumed to be stationary, i.e., constant over time. Several studies (e.g., Hsu (1977; 1982)), however, have found this to be an unreasonable assumption. Further, Chen and Keown (1981) have demonstrated that non-stationarity in a stock beta coefficient can lead directly to an overestimate of the unsystematic risk parameter. Accordingly, we adopt a time-varying coefficient model for β in our market modeling process, i.e.,

$$r_t = \alpha + \beta_t \cdot r_{mt} + e_t. \tag{2}$$

In principle, the β_t term may be modeled by any *ARMA*(*p*,*q*) process. However, most research indicates that an *AR*(1) process is sufficient. Accordingly, we extend the single index market model to a time varying coefficient regression (*TVCR*) model, which can be expressed as follows:

$$r_t = \alpha + \beta_t \cdot r_{mt} + e_t, \tag{3a}$$

where

$$\beta_t - \bar{\beta} = \phi(\beta_{t-1} - \bar{\beta}) + a_t, \tag{3b}$$

and ϕ is the backshift operator. We next adapt the market model to reflect potential heteroskedastic behavior of the error variance through time. Although most traditional event-study methods assumed a constant variance through both the pre- and post-event periods, some, like Brown and Warner (1985), have noted that if the variance is underestimated, the test statistic will lead to rejection of the null hypothesis more frequently than it should. Recently, a number of papers, including those by Connolly (1989) and Schwert and Seguin (1990), have analyzed the importance of adjusting for autoregressive conditionally heterskedastic (*ARCH*) effects in the residuals obtained from the conventional market models. It is argued that the ability to reliably form statistical inferences can be seriously compromised by failing to consider the *ARCH* error structure. Since the *ARCH* effect has been shown to be significant in many financial series, we take this into consideration in our model by applying the generalized autoregressive conditionally heterskedastic *GARCH*(1,1) model to the error or residual term. This yields a third potential market model, written as

$$r_t = \alpha + \beta_t \cdot r_{mt} + e_t, \tag{4a}$$

where $e_t|\psi_t \sim (0, h_t)$,

$$\beta_t - \bar{\beta} = \phi(\beta_{t-1} - \bar{\beta}) + a_t, \tag{4b}$$

where $a_t \sim (0, \sigma_a^{\ 2})$, and

$$h_t = \alpha_0 + \alpha_1 \cdot h_{t-1} + \alpha_2 \cdot e_{t-1}^{\ 2}. \tag{4c}$$

Overfitting tests can be performed for testing the order of β_t and the order of the variance equation.

2.2. Model Estimation

In the estimation stage, we use the maximum likelihood estimator. The likelihood function of the n set of observations, say, $y_1, y_2, \cdots, y_n$, is given by multiplying the conditional probability density functions since the observations are correlated; i.e.,

$$L(y;\theta) = \prod_{t=1}^{n} p(y_t | \psi_{t-1}),$$

where $p(y_t | \psi_{t-1})$ denotes the conditional distribution of y_t given the information set at time *t*-1. By the prediction error decomposition formula, the log-likelihood function of model (4a-4c) can be represented by innovations v_t and their variances f_t, both of which are functions of unknown parameters; e.g., $\theta = (\phi, \sigma_a^2, \alpha)$. Since v_t and f_t involve recursive terms, the Kalman filter technique is used to estimate the fixed parameters of the model, and to obtain therefrom prediction of future values. See Brockett and Chen (1994) for the mathematical details and proof of convergence of these estimates.

2.3. Identification and Diagnostic Checking

In the usual time series model, identification is a preliminary to estimation of the model. Here, we need to specify the three step model described earlier. Thus, identification of the adequate model will proceed in a number of steps as follow,

(i) the step 1 model (the simple market model),

$$r_t = \alpha + \beta_t \cdot r_{mt} + \varepsilon_t,$$

is identified and estimated by least squares in the ordinary regression model. Under the null hypothesis, the ordinary least squares (*OLS*) residuals $\hat{\varepsilon}_t$ should be white noise and uncorrelated with the regressor r_{mt}. Moreover, the squared residuals would also perform as white noise. Otherwise, the autocorrelation function (*ACF*) of residuals $\hat{\varepsilon}_t$ (or the *ACF* of squared residuals $\hat{\varepsilon}_t^2$) may suggest a misspecification problem. The test statistic

$$Q = n(n+2)\left(\frac{\sum_{k=1}^{m} r_k^2}{n-k}\right) \tag{5}$$

of Ljung and Box (1978) can be used to perform a statistical test to detect significant autocorrelation in the error (ε_t) series. The k^{th} autocorrelation coefficient of $\hat{\varepsilon}_t$ is r_k^2, and Q is distributed χ^2 with m degrees of freedom. If Q is statistically significant, we may proceed to employ the step-2 (or consider the *ARCH* effect) model, i.e.,

(ii) The random coefficients model,

$$r_t = \alpha + \beta_t \cdot r_{mt} + \varepsilon_t,$$

is estimated, where

$$\beta_t - \bar{\beta} = \phi(\beta_{t-1} - \bar{\beta}) + a_t.$$

Under the null hypothesis that there is no *ARCH*, we may (as shown in Li (1981)) use the conservative bounds of $2T^{-1/2}$ on the squared residuals. Consequently, if regression coefficients are stationary, the squared residuals may come directly from the step-1 model. However, if the time-varying regression coefficients are specified, the squared residuals may come from the step-2 model. Therefore, the first case leads to the estimation of a linear regression model with *GARCH* effects, and the second case involves the estimation of a time-varying regression coefficient model with *GARCH*. Once an adequate specification is available, the final step involves maximum likelihood estimation and testing based on the selected model.

Informal tests based on the *ACF*'s may be done for identification and diagnostics; however, we also present formal statistical tests as well. One such test is the likelihood ratio test, which is based upon a maximum likelihood approach. Two other tests (the Wald test and Lagrange Multiplier test) also have similar properties to the likelihood ratio test under a sequence of local alternatives.[4]

The likelihood ratio test is primarily concerned with testing the validity of a set of restrictions on the $n \times 1$ parameter vector, θ. The disadvantage of the likelihood ratio test is that the model must be estimated under both the null and alternative hypotheses. An alternative Lagrange Multiplier test procedure (see Harvey (1981)) is more attractive if the model is easier to estimate under the null hypothesis. The Lagrange Multiplier (*LM*) test statistic under the null hypothesis, which is asymptotically distributed χ^2_m, takes the form

$$LM = S(\theta_0)' I^{-1}(\theta_0) S(\theta_0),$$

where $S(\theta) = \frac{\partial \log L}{\partial \theta}$ is the score vector and $I(\theta) = E(\frac{\partial^2 \log L}{\partial \theta^2})$ is the information matrix, both of which are evaluated under the null hypothesis. Estimation under the more general restricted model is therefore avoided. The idea underlying the test is that when the null hypothesis is correct, the restricted estimate of θ_0 will tend to be near the unrestricted maximum likelihood estimate. Consequently, the first derivative, or $S(\theta_0)$, will be close to the zero vector. Under the

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[4] A more complete discussion may be found in a wide range of sources, including Cox and Hinkley (1979).

usual maximum likelihood regularity conditions, the *LM* statistic is asymptotically equivalent to the likelihood ratio statistic.

Since most traditional event studies use the single index, or step-1 market model, we would like to especially focus on this model. In this model, the null hypothesis assumes that β is not stochastic and that error terms e_t have constant variance. For non-stochastic β, we write

$$\beta_t = \bar{\beta},$$

which is fixed for all *t*. In terms of our general specification, the error term a_t in equation (3b) is identically zero, or σ_a^2 equals zero. Once β is taken to be fixed, the autoregressive coefficient ϕ becomes irrelevant. As there is no stochastic parameter variation, it does not matter what value is attached to this coefficient. This is described as follow:

$$H_{10}:, \boldsymbol{\alpha = 0,}\ \sigma_a^2 = 0,$$

versus

$$H_{11}: \alpha \neq 0,\ \sigma_a^2 > 0 \text{ (but specified } \phi = 0).$$

One difficulty associated with this problem is that the null hypothesis specifies a value on the boundary of the parameter surface — that is to say, we know that the variance σ_a^2 can not be less zero. When the parameter is interior to an open set in parameter space, Moran (1970) has shown that the *LM* test is equivalent to a likelihood ratio test. However, for the boundary situation, the two tests are no longer equivalent (see Chant (1974)). Chant notes that the usual inferential procedures based on likelihood ratio tests break down when the parameter lies on a boundary, but the *LM* test remains unaffected and retains its asymptotic properties (Chant (1974), section 4). Accordingly, we adopt the *LM* test for this problem. If the above null hypothesis (H_{10}) is not rejected, we adopt a step-1 model, whereas if the new hypothesis is rejected, we proceed to test the null hypothesis of a simple market model with *ARCH* effect:

$$H_{20}: \sigma_a^2 = 0$$

$$H_{21}: \sigma_a^2 > 0$$

When the variance equation includes the lagged conditional variance, it does not yield a standard regression result (See Breusch and Pagan (1978)). For this case, we adopt a regular *t*-test. The other choice when rejecting H_{10} is to test the null hypothesis of VCR model, which is,

$$H_{30}: \alpha = 0 \text{ versus}$$

$$H_{31}: \alpha \neq 0.$$

In this case, the log-likelihood function involves the recursive term $\beta_{t|t-1}$, which complicates the regression framework. Thus, we still adopt the likelihood ratio test or the regular *t*-tests. In Table 1, we summarize the model building procedure.

[PLACE TABLE 1 ABOUT HERE]

2.4. One-step-ahead Forecast Errors

Once the model is well specified by the data from the estimation period (pre-event window), the Kalman filter can be used to produce the one-step-ahead forecast errors, or innovations, for the post-sample (event period) data. By standardized one-step-ahead forecast errors, we mean

$$z_l = \frac{v_l}{\sqrt{f_l}} \qquad l \in \text{event period}$$

where v_l and f_l are the innovations and variances of the model (which are a function of the unknown model parameters). When the model is correctly specified and the model parameters are known, z_l are uncorrelated (or independent under normality) with mean 0 and unit variance. For instance, if the model is the simple step-1 model, the classical regression

$$r_t = \alpha + \beta_t \cdot r_{mt} + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{NID}(0,\sigma^2)$$

can be written in a state space form, in which the state vector $\boldsymbol{\alpha_t}$ and the transition matrix T are

$$\boldsymbol{\alpha_t} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix}, \text{ and}$$

$$T = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

There are no unknown parameters in system matrix, T, and therefore the one-step-ahead forecast errors produced by the Kalman filter technique in classical regression are uncorrelated and are equivalent to the *OLS* recursive residuals as in Brown, Durbin and Evans (1975). In the more usual case when the model parameters have been partly estimated, the z_l are only approximately uncorrelated with mean zero and variance σ^2. We adopt maximum likelihood estimation, since it is known to be consistent.

2.5. Cumulative Sum Test (*CUSUM*) -- To Overcome Event Date Uncertainty

In many cases, events may have a gradual, as opposed to sudden impact upon the market. Accordingly we shall utilize a technique (the cumulative sum, or *CUSUM* technique) which is sensitive to detecting the gradual shifting of the mean of the return series over time. This method was first introduced by Page (1954) in the context of continuous inspection schemes for quality control. Because the *CUSUM* technique makes use of information trends involving successive observations and not only single observations, this technique is more likely to detect a gradual change that takes place over time than other schemes used in the classical event study methodology.

Our purpose is to be able to reliably detect the effects caused by a specific event in a given return series. Initially, suppose that we can use as much information as possible in order to determine that no event effect is present in the data prior to time τ. Model parameters are estimated during the period incorporating the first τ - 1 observations. Thus, the estimators and the model structure will be unaffected by the event. Our null hypothesis assumes that the appropriate market model for assessing the "event effect" is the one that we inferred from using estimation period data, i.e., the model with the stochastic β and *GARCH* errors. The alternative hypothesis is that, due to the event, the response structure is different from the assumed one and that it is unrestricted. Hence, if the one-step-ahead forecast errors z_l are significantly far away from their expected null value of zero, this would indicate that the observations in the estimation period and the event period are generated from different models. Therefore, our proposed test statistic is based on z_l, and it takes the form

$$Z_r = \sum_{i=-t_1}^{r} z_i \qquad r = -t_1, -t_1 + 1, \cdots, t_2 \quad (6)$$

For convenience, we change the notation to (1,n), by letting n = t_2- (-t_1) +1 be the number of days in event-period window, 0 is denoted as the event day. Then

$$Z_r = \sum_{i=1}^{r} z_i \qquad r = 1,\ldots,n. \quad (7)$$

When the model parameters are known, Z_r obeys a student-*t* distribution, and a recursive *t*-test with normal distribution may be performed. However, the exact distribution for Z_r is unknown when the model parameters are partially estimated. Thus, we propose a portmanteau test instead of considering an exact distribution. To develop a portmanteau test, we use an invariance principle for random walks (Feller, 1970, pp. 342-3), which basically states that the asymptotic distribution of certain functions of random variables are insensitive to changes of the distributions of these random variables. Let

$$T = \max_{r \le n} |Z_r|. \quad (8)$$

Then, as $n \to \infty$,

$$\Pr\{\frac{T}{\sqrt{n}} \le t\} \to 4\pi^{-1} \sum_{k=0}^{\infty} (-1)^k (2k+1)^{-1} \cdot \exp\left\{\frac{-(2k+1)^2 \pi^2}{8t^2}\right\}. \quad (9)$$

Under the null hypothesis, the relationship depicted in (9) should hold approximately for moderate size n. For a given series, let $1\text{-}p^*$ denote the value computed from the right hand side of (9) with *t* given by

$$t = \max | Z_r | / \sqrt{n}. \quad (10)$$

That is, p^* is the observed significance level of the test. The test rejects H_0 at α level of significance if $p^* < \alpha$.

The graphical technique associated with the *CUSUM* also provides abundant information concerning the determination of <u>when</u> the return structure changed. The cumulative sums Z_r may be plotted sequentially to give a graphical method for detecting the approximate location of the "turning point". If there is no effect up to time $t = t_0$, $1 < t_0 < n$, but there is an effect from t_0 on, then the sample path of Z_r should perform a downward (negative) trend from zero starting at t_0. In other words, the turning point in the sequential plot of Z_r is roughly at t_0. Thus, the previous test statistic can be accompanied by a plot of *CUSUM* to visually verify the effect.

At a given level of significance α, a statistical assessment of the significance of the *CUSUM* graph is obtained by plotting two predefined values above and below the horizontal axis corresponding to the likelihood of boundary crossing by *CUSUM* of these lines being exactly α. Brown *et al.*(1975) derived the equation of these boundary crossing lines as

$$y = \pm [d+c\,(t - 1)]$$

for some t in (1,n), where $d=a\sqrt{n-1}$, $c = 2a/\sqrt{n-1}$, and a can be solved from the equation

$$Q(3a) + \exp(-4a^2)(1 - Q(a)) = 1/2\cdot\alpha, \tag{11}$$

where

$$Q(z) = \frac{1}{\sqrt{2\pi}}\int_z^\infty \exp(-\frac{1}{2}u^2)\,du.$$

One rejects the hypothesis of no trend (zero effect or no event effect) at level of significance α if the plotted *CUSUM* graph crosses either of the two prespecified lines. Useful pairs of values of a and a are

$\alpha = 0.01$, $a = 1.143$
$\alpha = 0.05$, $a = 0.948$
$\alpha = 0.10$, $a = 0.850$.

For a one-tailed test, one would take the significance level as α in (11), instead of $\alpha/2$ as used in a two-tailed test.

2.6. Simulation Examples

In order to illustrate the technique as well as the graphical methodology associated with the *CUSUM* plot, we simulate several different market models in the following examples.

Example 1: Simple market model. We simulate the series in which the beta changes in event period. In the following data sets, we choose the size of the estimation period to be 100, and, the size of the event-period window to be n = 30. The postulated model is

$$y_t = x_t + \varepsilon_t \qquad t = 1,2,\ldots,105,$$

$$= -3.0 + 2.0 \cdot x_t + \varepsilon_t \qquad t = 106,\ldots,130.$$

where the ε_t's are unit normal and the x_t's have a uniform distribution (0,1). As can be seen in Figure 1, the turning point is about at the sixth observation in the event period (the 106th time point). After this turning point, the *CUSUM* plot exhibits a trend (upward in this case). The precise p* value calculated from equation (9) (with t given by equation (10)) is 0.0025.

[PLACE FIGURE 1 ABOUT HERE]

Example 2: This example is similar to example 1, but it does not consider any 'changing point'; i.e., the model is

$$y_t = x_t + \varepsilon_t \qquad t = 1,2,\ldots,130.$$

The *CUSUM* plot for example 2 is shown in Figure 2. In this case, the plot does not exhibit any evidence of a persistent trend, and the p* value calculated from equation (9) (with t given by equation (10)) is 0.865, indicating that there are no significant changes.

[PLACE FIGURE 2 ABOUT HERE]

Example 3: Step-2 model: VCR model. Here the postulated model is

$$y_t = \beta_t x_t + \varepsilon_t \qquad t = 1,2,\ldots,105,$$
$$= -10 + \beta_t x_t + \varepsilon_t \qquad t = 106,\ldots,130,$$

where the stochastic risk parameter β evolves according to

$$\beta_t - 2 = 0.3\,(\beta_{t-1} - 2) + a_t \qquad a_t \sim \text{NID}(0,1).$$

The *CUSUM* plot for example 3 is shown in Figure 3. Again, a clear downward trend begins around the sixth point, and the p* value is equal to 0.003.

[PLACE FIGURE 3 ABOUT HERE]

3. An Empirical Study

Next, we apply the methodology outlined in the previous section of the paper to an investigation of the financial implications associated with the passage of California's Proposition 103. Proposition 103 provides a unique opportunity to empirically examine the impact of a well-publicized regulatory change on the stock market values of a regulated industry (specifically, property-liability insurance industry). Because Proposition 103 was extremely well publicized over an extended period of time, this particular event provides a nearly ideal setting for comparing our methodology with the classical event study methodology.

Next, we provide some background information on Proposition 103, and discuss the sample design and data analysis. The results obtained using our methodology are also reported and compared with the results of other studies that have applied the classical event study methodology to this particular event.

3.1. The Background Behind California's Proposition 103

On November 8, 1988, the voters of California narrowly passed Proposition 103, a referendum that mandated substantial changes in the manner in which the state's automobile insurance market was to be regulated. Specifically, this referendum called for all insurance rates to be rolled back by 20 percent below November 1987 levels and froze rates at those levels until November 1989. It also changed the state's long-standing competitive rating law to a prior approval law, granted an additional 20 percent "good" driver discount, and attempted to reduce insurance prices for urban drivers by eliminating or reducing reliance on "territorial rating".[5] As a result, California abandoned a market-oriented pricing system for a heavily regulated system. The passage of Proposition 103 marked the culmination of a bitter struggle between consumer groups, which favored the change, and the insurance industry, which opposed it.

The impetus behind Proposition 103 was partly due to a "cost crisis" in the market for automobile insurance. During the three years preceding the referendum, the cost of automobile insurance in California increased by 40 percent.[6] Representatives of the industry argued that

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[5] Quite interestingly, while Proposition 103 passed by a very close overall margin of 51 to 49 percent, 51 of the 57 counties in California voted against it. Most of the vote in favor of the initiative came from 6 highly urbanized counties surrounding Los Angeles and San Francisco. Since claims tend to be more frequent and severe in urban areas, it should come as no surprise that voters in these areas would vote in favor of a statute which (by deemphasizing territorial rating) would essentially create a wealth transfer from rural to urban drivers.

[6] While this would appear to be a rather substantial increase in costs, it is instructive to note that over this same period, a similar "crisis" was occurring nationwide. Cummins and Tennyson (1992) note that from 1984-1989, the auto insurance CPI grew at a 9 percent annual rate nationwide, compared to a 3.5 percent annual rate for the all-items CPI.

higher insurance rates were justified because operating costs had been driven up steadily rising medical fees and increased litigation. In addition, declining interest rates during this same period had reduced insurance companies' investment income.

Both consumer and industry organizations devoted substantial effort to preparing for the referendum. The Insurance Initiative Company Committee, a lobbying group that represented insurance companies industry more than 90 % of the premium volume underwritten in California, spent over $60 million to defeat Proposition 103. Consumer advocates (including Ralph Nader, Common Cause, and the Consumer Union) spent $2.2 million to convince voters of the merits of the referendum.

Proposition 103 promised to provide short-term benefits for the consumers. The most immediate attraction was the 20 percent reduction and freezing of automobile and other insurance rates for one year. Since consumers appeared to have such a large financial advantage from the enactment of Proposition 103, it is likely that the insurance industry suffered. However, an alternative view expressed by some groups is that the regulatory changes instituted in the aftermath of Proposition 103 may ultimately <u>benefit</u> the insurance industry. For example, some industry experts argue that by superimposing a “fair return” standard onto Proposition 103 (see Hill and Celis, 1989), the courts may have provided the industry with a loophole that may largely negate the 20 percent rate reduction provision.[7] In Table 2, we summarize the main features of the proposition ballot on November 8, 1988.

[7] As originally passed, Proposition 103 only exempted firms on the brink of insolvency from having to comply with the 20% rate rollback. In a subsequent decision on the constitutionality of Proposition 103, the California Supreme Court struck down the insolvency exemption rule, and replaced it with a “fair return” standard. What constitutes a fair return, on what basis it should be calculated, and how it should be applied to individual companies continues to be the subject of considerable litigation.

While the debate over the effect of Proposition 103 on the insurance industry continues,[8] several empirical studies have been done which have examined how the initiative effected the shareholders of property-liability insurers. Next, we briefly summarize results from previously published studies.

3.1.1. Empirical studies regarding Proposition 103

To date, three studies have investigated the market impact of Proposition 103, each using a variant of standard event study methodologies assuming a known event. Fields, Ghosh, Kidwell and Klein (1990) studied the market reaction of 36 property-liability firms, most with substantial exposure in California to capture the market's reaction to the November 8, 1988, election results. They calculated cumulative abnormal returns over a one-hundred and one day period (-65, +35). Negative cumulative abnormal returns were observed over a forty-six day period (-20, +25). They suggest that this is evidence of a sustained market revaluation. However, it is quite plausible that this proposition would simultaneously affect return and risk, in view of changes such as the abolition of territorial rating, the elimination of certain antitrust exemptions, and the mandating of a "good driver" discount). No β adjustment mechanism is employed by Fields *et al.*; therefore, a shift in systematic risk and a market reaction are not simultaneously recognized.

In a related study, Szewczyk and Varma (1990) performed an event study in which they measure not only the market reaction to the passage of Proposition 103, but also to a subsequent California Supreme Court ruling that upheld most of the provisions of Proposition 103. In this study, a classical methodology was used with a three day (-1,+1) and twenty-one day (-10 ,+10)

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[8] Gastel (1994) provides an excellent discussion of the history of Proposition 103 and the continuing debate associated with it.

event window. They conducted their study on a sample consisting of seventeen property-liability firms with significant exposure in California, twenty-five randomly selected property-liability firms with no California exposure and twenty-five non-insurance firms. Like Fields *et al.*, Szewczyk and Varma reported a significant negative reaction for all insurers, but a more pronounced reaction for those with California exposure.

In an effort to extend the previous two studies, Shelor and Cross (1990) expanded the sample of firms used by Fields *et al.* to include more firms without significant California exposure. This study used a twenty-one day (-10, +10), but unlike the previous studies, Shelor and Cross found a significant negative market only for firms without appreciable California exposure. They attribute the differences of their results to their large samples, to a different β estimation interval and to the use of firm size as a control variable.

What these studies have in common is that they focus attention upon the election itself. None of these studies provide any information concerning the timing of the actual market anticipation of the event. Our methodology provides a means for deciding the real "event day"; i.e., the day on which the market began to react. Next, we outline the timing of events associated with the passage of Proposition 103.

3.1.2. The timing of events

Proposition 103 received extensive news coverage before the election. The first national coverage of the bill came on June 8, 1988, when it was discussed in the *Wall Street Journal* (*WSJ*). However, on October 25 (two weeks prior to the election), The *Los Angeles Times* (*LAT*) predicted that Proposition 103 had a good chance of being approved, and on Saturday, November 5, released a poll showing that voters favored the measure by a 12% margin.

The final vote on the proposition was close, with 51% in favor and 49% opposed. As would be expected, the returns indicate substantial support for the law in densely populated areas and little support in rural districts. (The elimination of territorial rating under Proposition 103 would lower the cost of automobile insurance for urban drivers while increasing costs for rural motorists.)

Following the election the insurance industry filed a suit challenging the law, and the California Supreme Court blocked the law's implementation in order to consider its constitutionality. In mid-November 1988, Standard & Poor's and Moody's expressed concerns about the financial implications of Proposition 103 for insurers operating in California. Table 3 provides a chronology of key events related to the proposition.

3.2. Sample design and data

A sample of 52 publicly traded insurance companies with substantial involvement in property-liability insurance was selected from *A.M. Best's Aggregate and Averages.* (Many of the property-liability firms listed by *Best's* are subsidiary companies of parent firms. In these cases, the parent firm's stock prices are used in analysis). Any firm with confounding events such as a proposed tender offer, litigation, stock split, or takeover defenses were eliminated from the sample to control for other market distortions that might have been precipitated by these events. Those firms are also excluded from the sample, if the necessary financial data was incomplete. For firms listed on either the New York Stock Exchange (*NYSE*) or the American Stock Exchange (*ASE*), daily stock returns were taken from the Center for Research in Securities Prices

(*CRSP*) tape. Closing prices recorded in the "*NASDAQ* National Market Issues" pages of the *Wall Street Journal* were used for firms trading on the Over-The-Counter (*OTC*) market. The market return was measured using the *CRSP* unweighted index. The final sample consisted of 21 companies, 3 of which had no property-liability exposure in California. The sample firms are listed in Table 4.

The market reaction usually is better captured in price movements over time and not on a single event day. Thus, the duration of event-period should be determined first. The determination of the starting point of event period, or the endpoint of estimation period, must be carefully chosen so that the estimation period will not contaminate any potential effects due to the event. From Table 4, day -10, October 25, 1988 appears to be a good choice as the starting point. Also, in order to have a moderate event window size, a (-10,20) or thirty-one day window surrounding the election date of November 8, 1988 (labeled day 0), is selected for this study. Of course, the longer event period with a starting day much earlier than November 8 (day 0) can be constructed. We also performed an analysis using a 51-day (-30,20), event window, however the average residuals for the first 20 days was close to zero, reinforcing our choice of (-10,20). The expected daily return for each security was computed by observing the market behavior over a one-hundred and twenty trading day's interval prior to the event window, i.e., using return observations beginning 130 trading days before election day and continuing until 11 days before the event window.

3.3. Data Analysis

For each firm, the identification, estimation and diagnostic checking stages have been done to determine the final model for the estimation-period data. Simple market models are well specified for some of the firms, however, *ARCH* effect and nonstationary beta are presented for some firms, which indicate the traditional event-study using simple market model may be inappropriate and therefore causing some problems that we already mentioned. The models for each firm and diagnostic statistics (*LM* statistics, Box-Ljung *Q* statistic) are all shown in Table 5.[9] After employing the selected market model, the cumulative abnormal returns (standardized one-step-ahead forecast errors) during the event-period are examined. We hypothesized that Proposition 103 would have a negative effect on insurance-company stock prices, and calculated the p-values (equation 9) for each firm and the approximate timing when the firm's stock price reacted to the information, if the p-value were small enough to compare to the level. They are all shown in Table 6.[10]

3.4. Discussion

While most of the companies examined had negative standardized cumulative abnormal returns (*CAR*'s) during the event period, *CAR*'s were significantly negative (at 5% or 10% levels) for only 4 firms, or about 15% of the sample. The Proposition 103 studies cited earlier adopt the standard procedure of calculating cumulative abnormal returns across all firms, and all report a significantly negative market reaction to the passage of Proposition 103. However, we choose not to aggregate abnormal returns across companies, since both calendar and industry clustering[11]

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[9] For illustrative purposes, we have attached *ACF* and Partial *ACF* plots for Amwest Insurance Company and Orion Capital Corp. in Figures 6-13.

[10] *CUSUM* plots for a company showing a significant effect (the Progressive Group) and for a company showing a non-significant effect (Travelers Corp.) are exhibited in Figures 4 and 5.

[11] Calendar, or "event" clustering refers to a situation when the event being considered occurs at or near the same time for all of the firms in the sample. Industry clustering refers to events concentrated in the same industry. Industry clustering and event clustering are known to reduce the power of the traditional event study methods (see Dyckman, Philbrick and Stephan (1984)).

problems exist. Nevertheless, general inferences may be drawn, since 85% of the firms showed no significant negative effect.

The *CUSUM* plots revealed that the turning points are not at the election day itself. For example, Progressive Group exhibited a significant price decline October 25 (day -8), when the *Los Angeles Times* suggested that Proposition 103 was more likely to pass (see Figure 4). We also examined whether there may be a firm-specific characteristic that might explain why certain firms have significant (negative) effects while others do not. Shelor and Cross concluded that small firms were more exposed to the potentially negative consequences of Proposition 103 than large firms. However, we (like Fields *et al.*) fail to detect a size effect. In addition, when we reviewed the major characteristics of Proposition 103 (see table 2), we found that the initiative's key provisions involved a number of regulatory restrictions on the California automobile insurance market (such as the "good driver" discount and the territorial rating limitation). Therefore, we decided to investigate whether firms that concentrate their books of business in the automobile insurance market were more significantly affected by Proposition 103 than firms specializing in other lines of business. We collected data from *A. M. Best*'s Premium-Loss-Expense database on automobile premiums written (*APW*) and total premiums written (*TPW*) during 1987, and calculated the ratio *APW*% = *APW*/*TPW* for each firm in our sample. This information is presented in Table 7.

Next, we compare a firm that had a significantly negative reaction to Proposition 103 (Progressive Group (p-value =.047)), with a firm that reacted (Amwest Insurance Company (p-value = 0.32)). Progressive Group is primarily an auto insurer (its *APW*% equals 96.26%), whereas Amwest specializes in lines of business other than auto insurance (its *APW*% is 0). This dichotomy suggests that *APW* might be a potential explanatory variable for determining the market reaction to Proposition 103. Upon further examination however, the significance of this variable is questionable. For example, Hanover Insurance did not experience a significant stock price reaction to Proposition 103; yet over half of its business is in automobile insurance. However, when we investigate this particular company further, we find that the proportion of total premiums written by Hanover in California is quite small. This finding suggests that our *APW*% variable may be too aggregated; ideally, it would be helpful to be able to calculate an *APW*% in California variable for each company.[12] Unfortunately, such detailed information (premiums written by line and by state) is not available from data sources that we could access. However, from the previous discussion, we may conclude that *APW*% and the percent of total premiums written in California (*PW*%) are important proxy variables for use in investigating the impact of Proposition 103. Fields *et al.* also concluded that the total premiums written in California by a firm is a critical variable in explaining negative *CAR*. Shelor and Cross showed no significant impact on California property-liability or multi-line insurers while on occasion there was a significant negative impact on non-California firms. These two conclusions are extremely different.

It should be noted that our finding for the Amwest Insurance Company case is inconsistent with the results of Fields *et al.*, who showed that the Amwest Insurance Company had the largest negative *CAR* in their sample during a forty-day event window. This inconsistency may be due to the different event period, or due to the specification of an *ARCH* effect for Amwest Insurance Company data. Once the empirically verified *ARCH* effect for this firm is incorporated into the

[12] For the Progressive Group, the premiums written in California ranks first among the domiciles in which it is licensed.

model, it decreases the standardized residual and leads to the conclusion that Proposition 103 did not have a significant impact upon this firm's stock price.[13] Thus, we suspect that the inconsistent results may be due to model misspecification by Fields *et al*.

In summary, the major portion (85%) of publicly traded insurance companies in our sample showed no significantly negative effect to the passage of Proposition 103.

4. Conclusion

The classical event study methodology uses a simple market model for calculating abnormal returns and implicitly assumes that the security residuals are uncorrelated with a variance that is constant through both the estimation and the event periods. The test statistic used in the classical event study methodology is then simply the sum of the event-period abnormal returns divided by the square root of the sum of all securities' estimation-period residual variances. Under normality, independence, and stationarity assumptions, this test statistic has a student-*t* distribution that is used to assess the "significance" of the event. A number of studies have shown that the above statistical assumptions are inappropriate and impart a bias toward detecting event-related "effects," irrespective of whether such effects actually exist.

In this article, we developed a dynamic market model to obtain the expected returns of individual securities. This model takes into account certain known characteristics of financial time series, including time-varying beta, autocorrelated squared returns, and the fat-tailed property of daily return data. An autoregressive process with order 1, *AR*(1), is initialized for beta, and a *GARCH*(1,1) process is utilized to model the time-varying conditional variance.

[13] Note: FGKK utilized traditional event-study method, which assumes the (conditional) variance being constant over time. It might underestimate the variance.

For parameter estimation, a maximum likelihood approach is used. The estimation process is completed via a numerical optimization algorithm in conjunction with a Kalman filter technique, which makes the computation more efficient. Model diagnostic checking includes informal tools, such as Box-Jenkin's autocorrelation function (*ACF*) techniques, as well as formal test statistics such as the likelihood ratio test and the Lagrange multiplier test. In addition, the Kalman filter was used to produce one-step-ahead forecast errors, which are then used to develop excess return variables.

As in the classical event study methodology, the null hypothesis is that excess returns equal zero. Our test statistic is based on cumulative sum (*CUSUM*) of standardized one-step-ahead forecast errors. Under the classical step-1 regression model, the one-step-ahead forecast errors are equivalent to recursive residuals that appeared in Brown *et al.* (1975). It can be shown that they are uncorrelated and follow a standard normal distribution. However, for step-2 or step-3 models, the system matrices contain unknown parameters when representing the model as a state space form. In this situation, the property of lack of correlation still holds for large sample sizes, but the exact distribution of the *CUSUM* of standardized one-step-ahead forecast errors is unknown. Accordingly, we propose a portmanteau test statistic in equation (8) using an invariance principle for random walk, from Feller (1970). The power of the test statistic calculated using the classical event study methodology is usually affected by the length of event period; the longer the event window, the lower the power of test. However, in equation (8), the length of event window becomes less critical. Furthermore, a plot of the *CUSUM* can illustrate the approximate day when the market begins reacting to the new information. Simulation examples were given to show how the *CUSUM* plots behaved both when there is no change, and when there is a change in the step-1 and step-2 market models.

We have applied our new methodology to an examination of the effect of the passage of California's Proposition 103 on the prices of insurance stocks. This effect previously has been investigated using classical event study techniques. Because Proposition 103 was extremely well publicized over an extended period of time, this particular event provides an ideal setting for comparing our methodology with the previous studies that employed the classical event study methodology. Twenty two publicly traded property-liability insurers, most with a significant business presence in California, were chosen for the study. The step-1 model is well specified for some of the firms, however, time-varying beta or *ARCH* effect are specified for some firms. We investigated individual insurance companies, and found that only four firms had a significantly negative stock price reaction to the passage of Proposition 103. We also found that some firms, such as the Amwest Insurance Company, had not significant reaction to Proposition 103. This result stands in stark contrast to the results of a previous study by Fields *et al.* We believe that the source of inconsistency is due to the fact that the Fields *et al.* study did not incorporate the *ARCH* effects.

Our study suggests that the application of the classical event study methodology, without checking the behavior of security returns for stochastic beta and *GARCH* effects, may very well cause researchers to draw inappropriate conclusions.

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TABLE 1
Model Building Procedure

	Identification	Estimation	Diagnostic Checking
odel		least squares	*ACF* of LM_1 test
	ACF of from step-1 model, *CCF* of ,	maximum likelihood	*t*-test, *ACF* of *ACF* of
with ı	*ACF* of	maximum likelihood	*LR* test and *t*-tests *ACF* of residuals from *GARCH* equation
	From previous steps	maximum likelihood	From previous steps

TABLE 2
Major features of Proposition 103 ballot on Nov. 8, 1988*

Rate rollback	Insurers are required to reduce immediately rates on all insurance other than workers' compensation and ocean marine to 20%. In the next year the insurance commissioner can allow increase only if the insurer is threaten with insolvency.
Regulation of rates	All new rates are to be approved in advance by the commissioner. The burden of demonstrating the need for any proposed increase rests with the insurer.
Good-driver discount	Drivers with no more than one conviction for a moving violation can purchase auto insurance at a 20% discount from regular rates.
Elected commissioner	The insurance commissioner will be elected by popular vote rather than being appointed by the governor, and may not be an officer, agent, or employee of an insurer or have a financial interest in any insurer or licensee.
Taxes	The state premium tax will be adjusted so that the total amount of tax collected will remain constant after the reduction in premium.
Antitrust	The antitrust exemption of the insurance industry is repealed.
Rebates	The restriction on agents providing rebates to consumers is lifted.
Amendments	Changes to this act may be made only through popular vote.
Banking	Banks will be allowed to sell insurance.
Rate making	Territorial rating will be limited. The primary factors affecting rates will be driving characteristics of the insured.
Proponents	Ralph Nader, AFL-CIO, Consumers Union.
Opponents	Insurance industry, Chamber of Commerce, Gov. Deukmejian, Insurance commissioners.
Final vote	51% favorable, 49% against (referendum passed).

* **Source:** This table is adapted from Fields *et al.* (1990), Table 1, p. 236.

TABLE 3

Chronology of key press reports relating to California's Proposition 103 ballot on Nov. 8, 1988.*

Date	Trading days relative to election day	Press report
10/25	-10	Several polls indicated that Proposition 103 is leading the rest of the initiatives and more likely to pass. (*LAT*)
11/5	-1	California Field Poll indicates that 49% favor, 37% oppose, and 14% are undecided. (*LAT*)
11/7	-1	Negative impact on insurance industry stocks is expected if proposition is approved. (*WSJ*)
11/8	0	Election day.
11/9	+1	Final results show Proposition 103 wins by 200,000 votes. The insurance industry files court challenge to Proposition 103. (*LAT*)
11/10	+2	Consumer advocate groups threaten to move campaign into other states. (*WSJ*)
11/11	+3	Insurance companies threaten to withdraw from California market. (*WSJ*)
11/14	+4	S & P indicates a probable reduction in credit in the credit ratings of insurers doing business in California. (*WSJ*)
11/18	+8	Moody's indicates that Proposition 103 means financial concern for insurance firms. (*LAT*)
11/22	+10	Consumers in other states launch efforts to reduce insurance rates. (*WSJ*)

*__Source:__ This table is adapted from Fields *et al.* (1990), Table 2, p. 237.

TABLE 4
Property-Liability Insurers in the Sample

Firm	Ticker Symbol	Exchange
Amwest Insurance Company	AMWEST	NYSE
Aetna Life and Casual	AET	NYSE
Transamerican	TRANS	NYSE
American General Corp.	AGC	NYSE
Chubb Corp.	CHUB	NYSE
Cigna Corp.	CIG	NYSE
CNA Financial Corp.	CNA	NYSE
Continental Corp.	CIC	NYSE
Lincoln National Corp.	LIN	NYSE
Orion Capital Corp.	ORION	NYSE
Progressive Group.	PROG	NYSE
Teledyne Inc.	TDY	NYSE
Travelers Corp.	TRAV	NYSE
USF & G Corp	USFG	NYSE
Xerox (Crum/Forster)	XEROX	NYSE
Belvedere Corp	BELV	NYSE
Hanover Insurance	HINS	OTC
Ohio Casualty	OHCA	OTC
Safeco Corp	SAFC	OTC
St Paul Co. Inc.	STPC	OTC
Seibel Bruce Group	SEBG	OTC

TABLE 5 -- Final Models*

Firm			ϕ				
AMWES	1.2E-4 (.0019)	1.054 (.391)	0.332 (.956)	.21E-2 (.0019)	.24E-19 (.0003)	0.8339 (.014)	0.2112 (0.0243)
AET	5.1E-4 (.0012)	1.716 (.259)	-0.114 (0.2675)	.102E-5 (0.0011)	.023E-7 (.0229)	0.975 (0.015)	0.03 (0.016)
TRANS	-0.3E-4 (.0008)	1.696 (.178)	0.846 (.987)	0.27E-2 (.5E-2)	0.14E-8 (.003)	0.3885 (0.0167)	0.143 (0.0089)
AGC	9.0E-4 (.001)	1.427 (.215)	0.99 (1.0)	0.14E-7 (.304)	0.34E-9 (.0047)	0.8469 (.0098)	0.1869 (.013)
CHUB	2.5E-4 (.0001)	1.235 (.2087)	-0.98 (1.72)	0.24E-9 (0.0008)	0.17E-9 (0.0006)	0.9264 (0.046)	0.0735 (0.0408)
CIG	8.4E-4 (.001)	1.262 (.21)	0.1796 (1.006)	.14E-10 (0.0032)	.34E-12 (0.0003)	0.882 (0.0297)	0.154 (0.04)
CNA	-1.8E-4 (.0012)	1.966 (.256)	-0.87 (1.53)	.14E-9 (0.996)	.867E-7 (.998)	0.921 (0.024)	0.0852 (0.024)
CIC	7.6E-4 (.0008)	0.926 (.166)	0.859 (.578)	0.054 (0.04)	0.021 (0.0044)	0.22E-9 (0.015)	2.34 (0.01)
LIN	5.1E-4 (.0012)	1.716 (.259)	-.997 (1.21)	0.2734 (.0053)	0.3932 (0.0051)	0.22E-6 (0.0539)	6.476 (0.112)
ORION	1.5E-4 (.0012)	0.648 (.261)	-0.62 (3.32)	.139E-5 (0.859)	.278E-9 (0.759)	0.897 (0.096)	0.119 (0.1)
PROG	2.1E-4 (.0003)	0.328 (.112)	0.472 (0.031)	0.23E-5 (0.0043)	.145E-3 (0.432)	.36E-7 (0.0654)	.15E-3 (.0067)
TDY	-4.9E-4 (.0006)	1.068 (.1176)	0.42 (0.0293)	0.62E-2 (0.0021)	.176E-3 (0.6E-4)	.22E-12 (0.0289)	0.17E-2 (.0098)
TRAV	3.4E-4 (.0009)	1.191 (.181)	-0.79 (1.264)	0.13E-6 (3.12)	.338E2 (21.57)	.22E-9 (0.992)	1.2 (7.13)
XEROX	0.4E-4 (.0009)	1.55 (.181)	-0.054 (1.849)	.27E-7 (0.404)	0.54E-4 (0.012)	0.886 (0.013)	0.128 (0.025)
BELV	1.8E-4 (.0026)	0.92 (.5472)	0.433 (0.978)	.54E-8 (.1E-5)	.203E-5 (.2E-4)	0.0749 (.0014)	0.0996 (.0023)
HINS	1.2E-3 (.0012)	1.274 (.385)	-0.999 (0.995)	.14E-8 (0.823)	.22E-10 (1.21)	0.34 (0.121)	0.16E2 (1.51)
OHCA	2.7E-4 (.0009)	0.797 (0.274)	0.054 (0.76)	.33E-5 (.4432)	.48E-3 (0.012)	0.64E-4 (0.086)	0.0038 (0.025)
SAFC	8.7E-4 (.0001)	1.4301 (.3596)	0.69 (0.876)	.14E-9 (.859)	0.278 (0.076)	0.0946 (0.018)	0.0476 (0.019)
STPC	-2.2E-4 (.001)	1.824 (.302)	-0.974 (1.0)	.14E-6 (0.996)	0.13 (0.038)	0.22E-7 (0.021)	0.306 (0.016)

SEBG	-2.5E-4 (.0016)	0.765 (0.508)	-0.031 (1.251)	.27E-5 (5.87)	0.54E-7 (1.003)	0.939 (0.02)	0.06 (0.019)

*The standard errors for each estimate are shown in parenthesis.

TABLE 6

Firm	LM_1	Q_6	Q^*_6	p*
AMW	40.21	0.273	0.00	0.32
AET	0.29	0.768	0.793	0.3
TRANS	0.31	0.806	0.204	0.32
AGC	2.04	0.72	0.03	0.13
CHUB	26.88	0.452	0.000	0.47
CIG	3.67	0.28	0.648	0.35
CNA	8.10	0.03	0.542	0.43
CIC	0.12	0.45	0.46	0.013
LIN	15.52	0.358	0.43	0.37
ORION	4.54	0.906	0.441	0.23
PROG	40.96	0.15	0.92	0.047
TDY	3.0	0.13	0.407	0.101
TRAV	4.7	0.365	0.56	0.55
USFG	7.2	0.12	0.524	0.55
XERO	0.552	0.22	0.132	0.55
BELV	10.68	0.436	0.251	0.45
HINS	19.68	0.41	0.03	0.43
OHCA	0.946	0.2	0.56	0.15
SAFC	0.912	0.4	0.648	0.11
STPC	2.328	0.2	0.4	0.43
SEBG	8.54	0.2	0.15	0.32

1. LM_1 refers to test H_0: $\sigma^2_a = 0$, $\alpha = 0$, v.s. H_a: $\sigma^2_a > 0$, $\alpha \neq 0$ (but specified $\phi = 0$)
2. Q_6 column refers to the probability for testing white -noise of residuals from step-1 model, Q_6^* has similar definition, but for testing white noise of squared residuals.
3. $\chi^2(3,0.05) = 7.81$, $\chi^2(2,0.05) = 5.99$, $\chi^2(3,0.1) = 6.25$, $\chi^2(2,0.1) = 4.61$

TABLE 7

Corp.	**APW%**	**PW% in California**
AMWEST	0.0	46.1
AET	32.84	9.0
TRANS	33.6	35.4
AGC	11.48	N/A
CHUB	11.66	14.4
CIG	19.27	12
CNA	21.02	11.7
CIC	20.07	9.0
LIN	34.97	10.9
ORION	26.10	18.6
PROG	94.76	23.4
TDY	15.23	7.1
TRAV	36.12	7.1
USFG	25.34	N/A
XERO	27.84	26.7
BELV	16.63	N/A
HINS	51.24	N/A
OHCA	46.54	22.1
SAFC	30.24	25.0
STPC	11.71	5.1
SEBG	31.92	0

Note: APW% is defined as the percentage of auto premiums written in proportion to the company's entire book of business. Auto premiums written includes auto liability and auto physical damage.

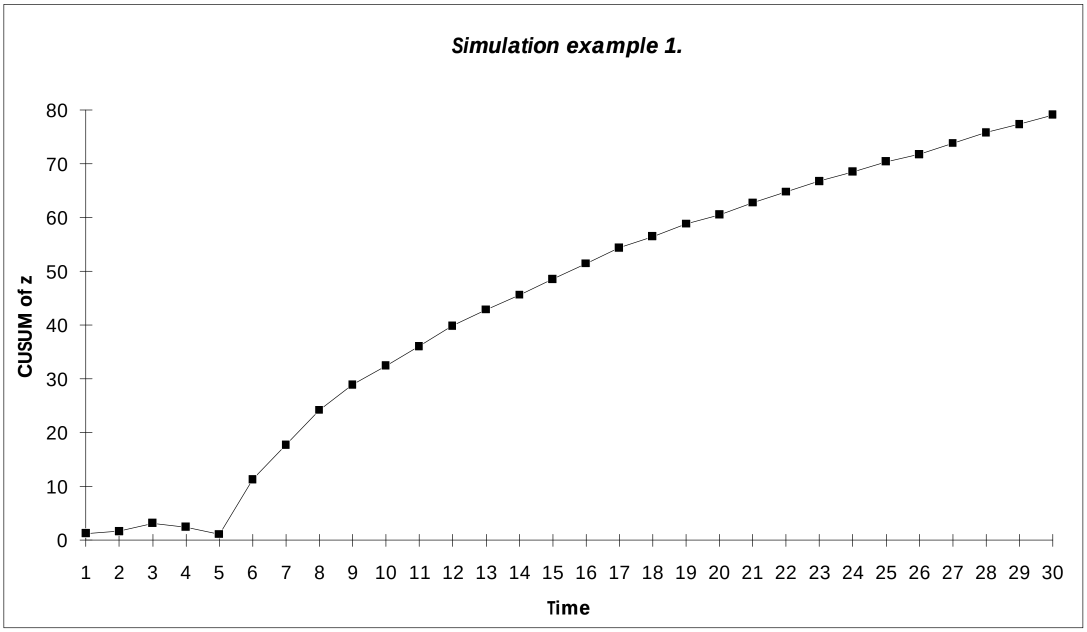

Figure 1. *CUSUM* plot where change occured at time 5.

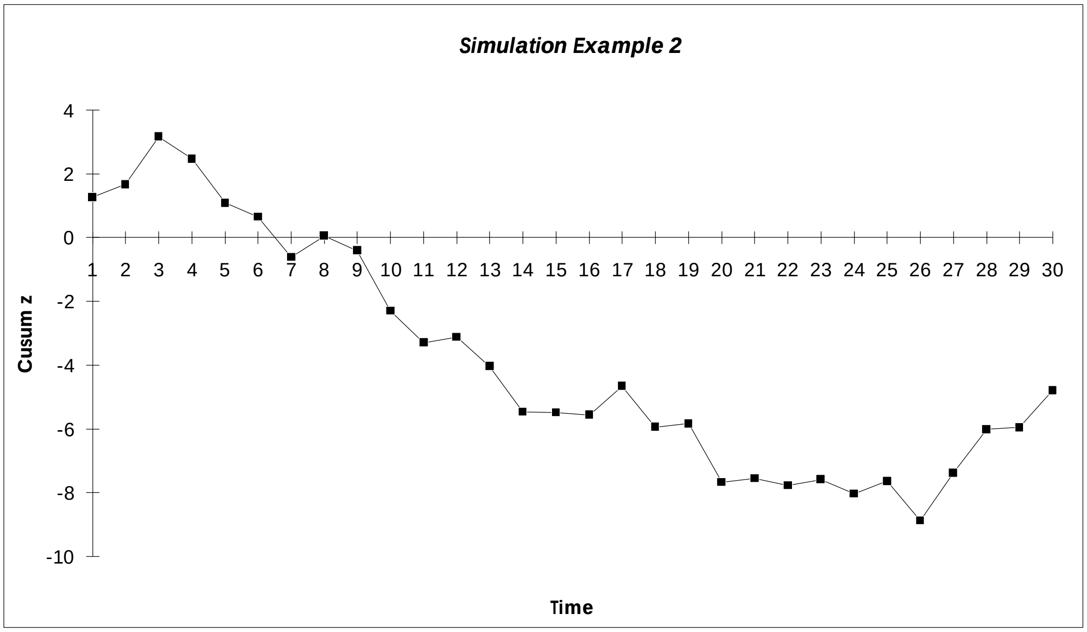

Figure 2. *CUSUM* plot where no change in structure occured.

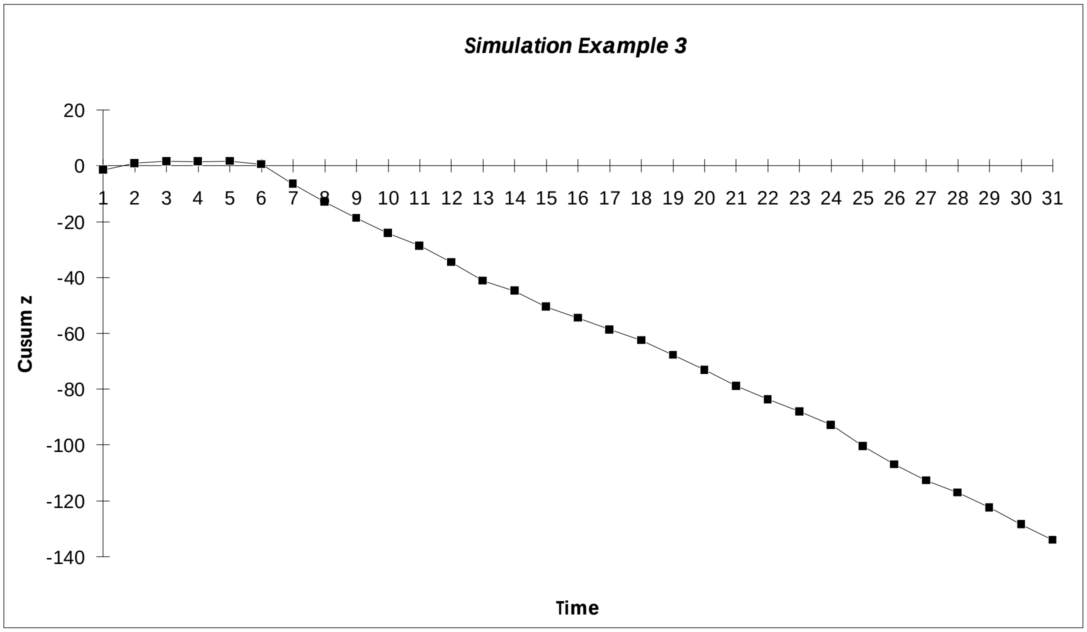

Figure 3. *CUSUM* plot with stochastic β and change occuring at time 5.

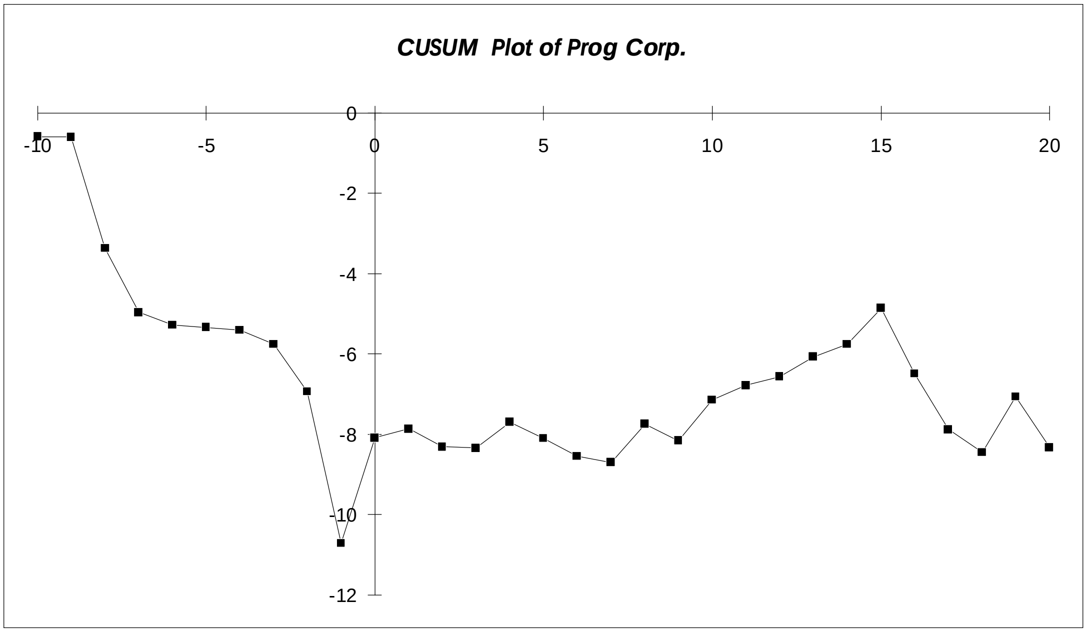

Figure 4. *CUSUM* plot of the Progressive Group, Inc.

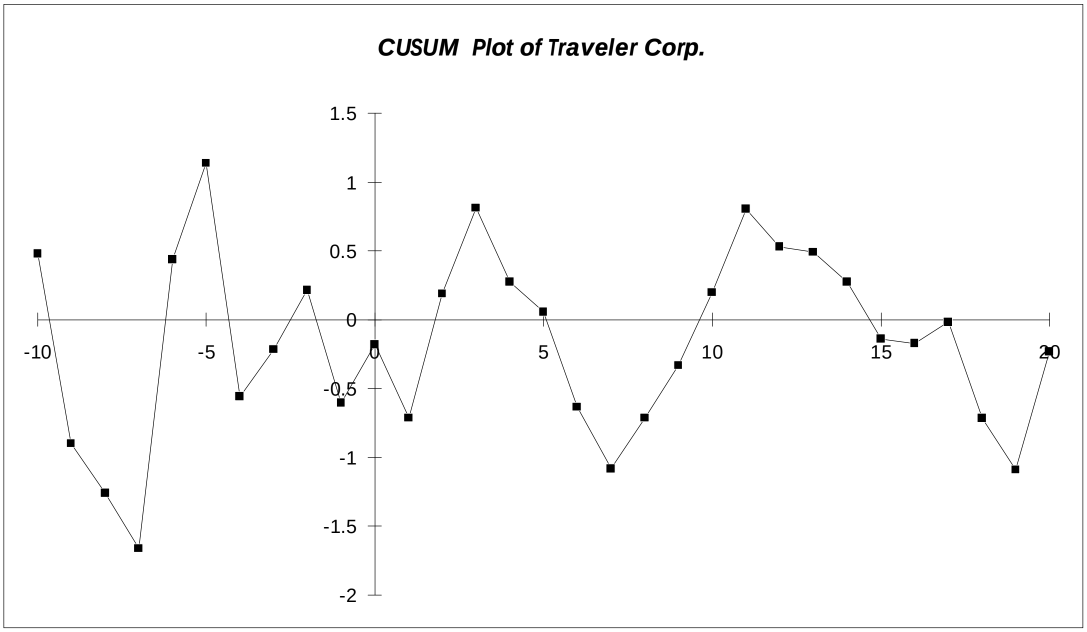

Figure 5. *CUSUM* plot of the Travelers Corp.

```
Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
  0 0.00017816     1.00000  |                    |********************|
  1  -6.165E-6    -0.03460  |                .  *|   .                |
  2  -0.000012    -0.06714  |                .  *|   .                |
  3 0.00001338     0.07508  |                .   |** .                |
  4 0.00001073     0.06023  |                .   |*  .                |
  5 -8.1171E-6    -0.04556  |                .  *|   .                |
  6  1.1377E-6     0.00639  |                .   |   .                |
  7 1.15565E-6     0.00649  |                .   |   .                |
  8 -9.7882E-6    -0.05494  |                .  *|   .                |
  9 2.68699E-7     0.00151  |                .   |   .                |
 10 -1.1124E-6    -0.00624  |                .   |   .                |
 11 -2.3916E-6    -0.01342  |                .   |   .                |
 12 -0.0000322    -0.18094  |                ****|   .                |
 13 4.65925E-6     0.02615  |                .   |*  .                |
 14 8.63411E-6     0.04846  |                .   |*  .                |
 15 2.56661E-6     0.01441  |                .   |   .                |
 16 -7.6807E-6    -0.04311  |                .  *|   .                |
 17 -0.0000101    -0.05686  |                .  *|   .                |
 18 -3.1458E-6    -0.01766  |                .   |   .                |
 19 -6.8217E-6    -0.03829  |                .  *|   .                |
 20 3.50329E-7     0.00197  |                .   |   .                |
 21 6.53483E-8     0.00037  |                .   |   .                |
 22  4.4161E-6     0.02479  |                .   |   .                |
 23 0.00001284     0.07209  |                .   |*  .                |
 24  4.6055E-6     0.02585  |                .   |*  .                |
```

Figure 6. The *ACF* of residuals from step-1 model (Orion Capital Corp.).

```
Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1   -0.03460  |                .  *|   .                |
   2   -0.06842  |                .  *|   .                |
   3    0.07065  |                .   |*  .                |
   4    0.06133  |                .   |*  .                |
   5   -0.03220  |                .  *|   .                |
   6    0.00611  |                .   |   .                |
   7   -0.00683  |                .   |   .                |
   8   -0.05303  |                .  *|   .                |
   9    0.00162  |                .   |   .                |
  10   -0.01493  |                .   |   .                |
  11   -0.00589  |                .   |   .                |
  12   -0.17993  |                ****|   .                |
  13    0.01032  |                .   |   .                |
  14    0.03281  |                .   |*  .                |
  15    0.04735  |                .   |*  .                |
  16   -0.02238  |                .   |   .                |
  17   -0.08058  |                . **|   .                |
  18   -0.03605  |                .  *|   .                |
  19   -0.04822  |                .  *|   .                |
  20   -0.00512  |                .   |   .                |
  21    0.00909  |                .   |   .                |
  22    0.02801  |                .   |*  .                |
  23    0.08007  |                .   |** .                |
  24   -0.00405  |                .   |   .                |
```

Figure 7. Partial Autocorrelations of residuals from step-1 model (Orion Capital Corp.).

Autocorrelation Check for White Noise

To Lag	Chi Square	DF	Prob	Autocorrelations					
6	2.14	6	0.906	-0.035	-0.067	0.075	0.060	-0.046	0.006
12	7.01	12	0.857	0.006	-0.055	0.002	-0.006	-0.013	-0.181
18	8.22	18	0.975	0.026	0.048	0.014	-0.043	-0.057	-0.018
24	9.41	24	0.997	-0.038	0.002	0.000	0.025	0.072	0.026

In the *ACF* and *PACF* plots, the dotted lines represent the limits. We can see that the autocorrelations (up to lag 24) are all within two standard deviation ±2/. *Q* statistics calculated for several lags, for instance 6, 12, etc. are not significant.

```
Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
  0 1.22499E-7    1.00000  |                    |********************|
  1 1.44691E-8    0.11812  |                .   |** .                |
  2 -3.6855E-9   -0.03009  |                .  *|   .                |
  3 8.27705E-9    0.06757  |                .   |*  .                |
  4  6.8873E-9    0.05622  |                .   |*  .                |
  5 1.78445E-8    0.14567  |                .   |***.                |
  6 6.33696E-9    0.05173  |                .   |*  .                |
  7 -1.2036E-8   -0.09825  |                . **|   .                |
  8 -3.8089E-9   -0.03109  |                .  *|   .                |
  9 1.91962E-9    0.01567  |                .   |   .                |
 10 -1.1835E-8   -0.09661  |                . **|   .                |
 11 -7.2707E-9   -0.05935  |                .  *|   .                |
 12 -5.2742E-9   -0.04305  |                .  *|   .                |
 13 -1.0192E-8   -0.08320  |                . **|   .                |
 14 -2.5426E-9   -0.02076  |                .   |   .                |
 15 -7.0308E-9   -0.05739  |                .  *|   .                |
 16  -7.089E-9   -0.05787  |                .  *|   .                |
 17 5.68194E-9    0.04638  |                .   |*  .                |
 18 4.80331E-9    0.03921  |                .   |*  .                |
 19 9.43088E-9    0.07699  |                .   |** .                |
 20 -2.6039E-9   -0.02126  |                .   |   .                |
 21 -6.1336E-9   -0.05007  |                .  *|   .                |
 22 1.04421E-8    0.08524  |                .   |** .                |
 23 -1.3529E-9   -0.01104  |                .   |   .                |
 24 -5.2965E-9   -0.04324  |                .  *|   .                |
```

Figure 8. *ACF* of squared residuals from step-1 model (Orion Capital Corp.)

```
Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1    0.11812 |                .   |** .                |
   2   -0.04466 |                .  *|   .                |
   3    0.07779 |                .   |** .                |
   4    0.03765 |                .   |*  .                |
   5    0.14331 |                .   |***.                |
   6    0.01695 |                .   |   .                |
   7   -0.10319 |                . **|   .                |
   8   -0.02805 |                .  *|   .                |
   9   -0.00366 |                .   |   .                |
  10   -0.11455 |                . **|   .                |
  11   -0.03563 |                .  *|   .                |
  12   -0.01429 |                .   |   .                |
  13   -0.05372 |                .  *|   .                |
  14   -0.00276 |                .   |   .                |
  15   -0.03150 |                .  *|   .                |
  16   -0.01507 |                .   |   .                |
  17    0.05430 |                .   |*  .                |
  18    0.04223 |                .   |*  .                |
  19    0.09282 |                .   |** .                |
  20   -0.05108 |                .  *|   .                |
  21   -0.04767 |                .  *|   .                |
  22    0.05834 |                .   |*  .                |
  23   -0.08099 |                . **|   .                |
  24   -0.05275 |                .  *|   .                |
```

Figure 9. *PACF* of squared residuals from step-1 model (Orion Capital Corp.)

Autocorrelation Check for White Noise

To Lag	Chi Square	DF	Prob	Autocorrelations					
6	5.84	6	0.441	0.118	-0.030	0.068	0.056	0.146	0.052
12	9.22	12	0.684	-0.098	-0.031	0.016	-0.097	-0.059	-0.043
18	11.68	18	0.863	-0.083	-0.021	-0.057	-0.058	0.046	0.039
24	14.37	24	0.938	0.077	-0.021	-0.050	0.085	-0.011	-0.043

Again, the squared residuals from step-1 model are checked by *ACF* and P*ACF* techniques. It was very clear pattern that the squared residuals exhibited white noise behavior.

```
Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
  0 0.00039995    1.00000  |                    |********************|
  1 0.00003799    0.09500  |                .   |** .                |
  2 0.00007596    0.18992  |                .   |****                |
```

```
   3 0.00002308    0.05771  |                .   |*   .                |
   4 0.00003618    0.09046  |                .   |**  .                |
   5  -0.000014   -0.03495  |                .  *|    .                |
   6 -0.0000213   -0.05318  |                .  *|    .                |
   7 -0.0000302   -0.07544  |                . **|    .                |
   8  -0.000027   -0.06749  |                .  *|    .                |
   9 7.59455E-6    0.01899  |                .   |    .                |
  10 -0.0001012   -0.25297  |               *****|    .                |
  11 -0.0000205   -0.05119  |                .  *|    .                |
  12 -0.0000181   -0.04528  |                .  *|    .                |
  13 0.00002866    0.07166  |                .   |*   .                |
  14 -0.0000332   -0.08313  |                . **|    .                |
  15 0.00001718    0.04295  |                .   |*   .                |
  16 5.39872E-6    0.01350  |                .   |    .                |
  17 0.00001106    0.02765  |                .   |*   .                |
  18 -0.0000525   -0.13129  |                .***|    .                |
  19 -0.0000349   -0.08721  |                . **|    .                |
  20 0.00001608    0.04019  |                .   |*   .                |
  21 -8.5474E-6   -0.02137  |                .   |    .                |
  22 -0.0000233   -0.05824  |                .  *|    .                |
  23 -0.0000814   -0.20355  |                ****|    .                |
  24 -3.0937E-7   -0.00077  |                .   |    .                |
```

Figure 10. *ACF* of residuals from step-1 model (Amwest Insurance Company)

```
Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1    0.09500  |                .   |**  .                |
   2    0.18255  |                .   |****                 |
   3    0.02674  |                .   |*   .                |
   4    0.05165  |                .   |*   .                |
   5   -0.06342  |                .  *|    .                |
   6   -0.07655  |                . **|    .                |
   7   -0.05777  |                .  *|    .                |
   8   -0.03861  |                .  *|    .                |
   9    0.06686  |                .   |*   .                |
  10   -0.24030  |               *****|    .                |
  11   -0.02268  |                .   |    .                |
  12    0.04210  |                .   |*   .                |
  13    0.09717  |                .   |**  .                |
  14   -0.06677  |                .  *|    .                |
  15    0.00797  |                .   |    .                |
  16    0.00444  |                .   |    .                |
  17   -0.02124  |                .   |    .                |
  18   -0.16594  |                .***|    .                |
  19   -0.05487  |                .  *|    .                |
  20    0.06282  |                .   |*   .                |
  21   -0.00764  |                .   |    .                |
  22   -0.07226  |                .  *|    .                |
  23   -0.17337  |                .***|    .                |
  24   -0.00101  |                .   |    .                |
```

Figure 11. P*ACF* of residuals from step-1 model (Amwest Insurance Company).

Autocorrelation Check for White Noise

To Lag	Chi Square	DF	Prob	Autocorrelations					
6	7.55	6	0.273	0.095	0.190	0.058	0.090	-0.035	-0.053
12	18.08	12	0.113	-0.075	-0.067	0.019	-0.253	-0.051	-0.045
18	22.60	18	0.206	0.072	-0.083	0.043	0.013	0.028	-0.131
24	30.77	24	0.161	-0.087	0.040	-0.021	-0.058	-0.204	-0.001

```
Lag Covariance Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
  0 6.07774E-7    1.00000  |                    |********************|
  1 2.51899E-7    0.41446  |                .   |********            |
  2 1.29636E-7    0.21330  |                .   |****                |
  3 -6.5688E-9   -0.01081  |                .   |   .                |
  4 1.08497E-8    0.01785  |                .   |   .                |
  5 -4.4713E-8   -0.07357  |                .  *|   .                |
  6 3.61642E-8    0.05950  |                .   |*  .                |
  7 9.28605E-8    0.15279  |                .   |***.                |
  8 1.89193E-7    0.31129  |                .   |******              |
  9 8.71742E-8    0.14343  |               .    |*** .               |
 10 4.31523E-8    0.07100  |               .    |*   .               |
 11 -5.3049E-8   -0.08728  |               .  **|    .               |
 12 -8.6082E-8   -0.14163  |               . ***|    .               |
 13 -5.5276E-8   -0.09095  |               .  **|    .               |
 14 -4.0571E-8   -0.06675  |               .   *|    .               |
 15 -6.0901E-8   -0.10020  |               .  **|    .               |
 16 1.44056E-8    0.02370  |               .    |    .               |
 17 -2.2651E-8   -0.03727  |               .   *|    .               |
 19 -7.0746E-8   -0.11640  |               .  **|    .               |
 20 -8.8528E-8   -0.14566  |               . ***|    .               |
 21   -6.33E-8   -0.10415  |               .  **|    .               |
 22  2.3338E-8    0.03840  |               .    |*   .               |
 23  7.9715E-8    0.13116  |               .    |*** .               |
 24 8.21358E-8    0.13514  |               .    |*** .               |
```

Figure 12. *ACF* of squared residuals from step-1 model (Amwest Insurance Company).

```
Lag Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1    0.41446  |                .   |********            |
   2    0.05013  |                .   |*  .                |
   3   -0.13988  |                .***|   .                |
   4    0.07126  |                .   |*  .                |
   5   -0.09115  |                . **|   .                |
   6    0.12712  |                .   |***.                |
   7    0.14490  |                .   |***.                |
   8    0.20043  |                .   |****                |
   9   -0.08987  |                . **|   .                |
  10   -0.02708  |                .  *|   .                |
  11   -0.08944  |                . **|   .                |
  12   -0.10426  |                . **|   .                |
  13    0.08222  |                .   |** .                |
  14   -0.08784  |                . **|   .                |
  15   -0.15042  |                .***|   .                |
  16    0.06846  |                .   |*  .                |
  17   -0.09479  |                . **|   .                |
  18   -0.04856  |                .  *|   .                |
  19    0.03546  |                .   |*  .                |
  20   -0.08903  |                . **|   .                |
  21    0.01207  |                .   |   .                |
  22    0.19472  |                .   |****                |
  23    0.12934  |                .   |***.                |
  24   -0.00199  |                .   |   .                |
```

Figure 13. P*ACF* of squared residuals from step-1 model (Amwest Insurance Company)

Autocorrelation Check for White Noise

To Lag	Chi Square	DF	Prob	Autocorrelations					
6	27.98	6	0.000	0.414	0.213	-0.011	0.018	-0.074	0.060
12	50.79	12	0.000	0.153	0.311	0.143	0.071	-0.087	-0.142
18	54.95	18	0.000	-0.091	-0.067	-0.100	0.024	-0.037	-0.071
24	67.22	24	0.000	-0.116	-0.146	-0.104	0.038	0.131	0.135

In the case of the Amwest Insurance Company, the residuals appeared to behave like white noise. However, the squared residuals are autocorrelated when checking from *ACF* and P*ACF* plots, and the Q statistics are significant. This preliminary checking causes us to check the *ARCH* effect in the Amwest Insurance Company return series.