THE EFFICACY OF EVENT-STUDY METHODOLOGIES: MEASURING EREIT ABNORMAL PERFORMANCE UNDER CONDITIONS OF INDUCED VARIANCE

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Abstract

Several papers have identified the hazards associated with event-induced variance, yet event studies continue to ignore the problem. This study demonstrates that the most commonly used abnormal return detection methods reject the null hypothesis of zero abnormal returns too often. This causes researchers to conclude the detection of abnormal performance when none is present. Two easy to employ alternative methods are proposed that are relatively unaffected by event-induced variance.

INTRODUCTION

Event studies have been the primary methodology used to assess the effect that the occurrence of an event has on the returns of a firm's common stock price since the seminal works of Ball and Brown (1968) and Fama, Fisher, Jenson, and Roll (1969). Brown and Warner (1980, 1985) compare the efficacy of different abnormal return detecting methodologies and the limitations of each. Two of the caveats of their work are that non-synchronous trading and event-induced variance cause existing detection methods to fail.

Equity Real Estate Investment Trusts (EREIT) return data is notoriously associated with non-synchronous trading [Goetzmann and Ibbotson 1990; Kuhle and Walther 1986; Ibbotson and Seigel 1984]. Non-synchronous trading causes serial correlation in abnormal returns which results in the breakdown of the most basic event study methodology assumptions [Brown and Warner 1985]. Thus, it is quite plausible that methodologies used in conjunction with the returns of large capitalization stocks may not yield reliable results for EREIT data, which is more comparable to small capitalization stocks [Han and Liang 1995; Myer and Webb 1994, 1993; Gyourko and Keim 1992; Hartzell and Mengden 1986; and Martin and Cook 1991].

Event-induced variance occurs when the variance during the event window exceeds the variance over the estimation period[1]. Several papers have confirmed this effect [Beaver (1968), Patell and Wolfson (1979), Dann (1981), Kalay and Lowenstein (1985), Rosenstein and Wyatt (1990)], while others have proposed methods to control for it [Charest (1978), Collins and Dent (1984), Ball and Torous (1988), Corrado (1989), and Boehmer, Musumeci, and Poulsen (1991)].

It is not uncommon for an event to cause an increase in the cross-sectional dispersion of a stocks' returns. Moreover, the degree of dispersion may vary tremendously from one firm to the next[2]. If researchers fail to control for these varying degrees of dispersion across firms, we will generally observe a variance increase on the event day. Such varying firm effects lead to an increase in measured cross-sectional dispersion that actually reflects our failure to control for all relevant return influencing factors. If the variance is understated, as has been found to be the normal case, we will reject the null hypothesis of zero abnormal returns more frequently than we should, even though the average abnormal return is significantly close to zero. Hence, many studies may appear to find abnormal performance due to a failure to consider event-induced variance.

The impetus for this study is twofold. First, no examination has been performed to determine which abnormal return detection methods are appropriate when performing event studies on securitized real estate, or EREITs. Since 1992, the EREIT market has exploded and has been growing at an exponential rate ever since. At this time, its size and distinction as an emerging classification of stock warrants its mainstream examination. Second, event-induced

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variance is ubiquitous, yet it is often ignored in event studies. While it is not the purpose of this paper to examine the cause of event-induced variance, proposed event study methodologies are evaluated with respect to varying levels of event-induced variance. Once it has been determined which methods provide the most accurate results under various conditions, future researchers will be able to choose the most appropriate methodology by matching the characteristics of their sample with the simulated characteristics of those allowed for in this study.

The organization of the remainder of the paper is as follows. Section II describes the experimental design used in the analysis. Various methodologies are discussed in section III. Results are show in section IV, and section V summarizes the most salient findings.

EXPERIMENTAL DESIGN

Alternative Performance Measures

Before abnormal returns can be measured, a benchmark used to define normal returns must be specified. Four general models have been considered: Mean Adjusted Returns, Market Adjusted Returns, Control Portfolios, and Risk Adjusted Returns[3]. Brown and Warner (1980, 1985) find that the Mean Adjusted Returns benchmark often works as well as more complex models[4]. In a more comprehensive comparison, Dyckman, Philbrick, and Stephan (1984) find that the Risk Adjusted method is superior. This study uses the single index version of the risk adjusted expected return generating model, which largely subsumes current event study research[5].

To combat the problem of non-synchronous trading, two widely accepted methods have been proposed. These methods are the Scholes and Williams (1977) beta(SW) and the Dimson (1979) beta. Fowler and Rorke (1983) show the effectiveness of these two methods to be relatively equivalent. When compared to the standard Ordinary Least Squares (OLS) approach, the SW and Dimson betas are found to be no more powerful [Reinganum (1982), and Theobald (1983)]. Moreover, Bartholdy and Riding (1994) conclude that OLS actually outperforms these two more involved methods of beta calculation, thus attenuating the argument that methods beyond the traditional OLS method should be used. For this reason, OLS estimates will be used throughout the analysis.

In theory, the correct identification of the "true" return generating process is important in event studies because the more predictable the returns are over the event window, the easier it will be to detect abnormal performance[6]. Measures used to detect abnormal performance are derived from hypothesized properties possessed by actual financial data. Therefore, if the true return generating processes were known, the various proposed abnormal return generating processes could be evaluated by examining their respective properties and assumptions relative to the true characteristics of returns. However, since the actual data used in event studies follows a process which is unobservable, such a theoretical comparison is not possible. For this reason, the relative performance of alternative abnormal return detecting methodologies is strictly an empirical question.

Sample Creation

250 portfolios each containing 50 EREITs are created. Each event date is chosen at random, with replacement, and with an equal probability of selection, from all EREITs listed on the 1995 Center for Research in Security Prices (CRSP) Daily Returns File from July 1962 through December 1995. The estimation period extends from time(-249 through -6) while the event window includes the eleven days from (-5 through +5). To remain in the sample, 30 daily EREIT returns must be observed at any time during the estimation period and all eleven daily EREIT returns must be observed during the event window.

Simulating Abnormal Returns

The 12,500 event dates used in the final sample are selected at random points in time, thus there is no reason to believe that any of them contain any systematic abnormal performance. Since the paper's focus is on the ability of various methods to detect abnormal performance, it is necessary to specify a procedure which will introduce a known and quantifiable level of abnormal returns.

Abnormal performance is simulated by adding a constant to the returns observed on the event date[7]. For example, to introduce an abnormal return of 2%, the constant .02 is added to the day 0 return. Abnormal returns of 0%, 1%, and 2% are examined.

Simulating Event-Induced Variance

Again, since all of the event dates selected do not correspond to actual events, there should be no systematic increases in variance associated with any of the samples. To study the effects of event-induced variance, a procedure must be used to introduce variance. The variance during each event window follows the form of $k_i \acute{o}^2$. Here, $\acute{o}^2$ is the observed variance over the estimation period[8] and k_i is a constant used to artificially alter the variance by factors of 0, .5, 1, and 2.

METHODOLOGIES

Market Model Residual Test

This is the standard regression residual test. The returns for each security are regressed against the returns on the market over the estimation period. This results in a residual which is referred to as the security's abnormal return. This basic method does not consider the cross-correlation of residuals over time, nor does in take into consideration the possibility of event-induced variance.

Standardized Residual Test

This model, originated by Patell (1976) and used in Brown and Warner (1985), is similar to the market model residuals test in that residuals are formed in the same manner. However, they are normalized or "standardized" before the portfolios are formed. While this method still assumes residuals are uncorrelated and event-induced variance is insignificant, it does take into account the out-of-sample prediction error and further allows for heteroskedasticity in event window residuals. The adjustment made in this method helps prevent a few securities with large sample variances from driving the results.

Cross-Sectional Test

Charest's (1978) cross-sectional method assumes that cross-sectional residuals are uncorrelated, but does not require a lack of event-induced variance provided the sample residuals come from the same distribution. This method is examined independently as well as in conjunction with the standardized residual test, as suggested by Boehmer, Musumeci, and Poulsen (1991).

Standardized Cross-Sectional Test

This method is a hybrid between the standardized residual test and the cross-sectional method. First, residuals are standardized, as previously described, then these standardized residuals are applied in the cross-sectional method in place of traditional unstandardized residuals. Benefits from both methods are realized. Information from the estimation period is used and event-induced variance does not decrease the power of the test. The assumption of uncorrelated residuals, however, does remain.

Sign Test

The sign test is a non-parametric, binomial test used to verify that a few firms are not responsible for the results. The problem with this test is that it assumes half of the security returns will be negative when in fact a majority should be positive. This test alone is not powerful enough to yield reliable conclusions and is therefore designed to be used in connection with other procedures such as the market model residual and standardized residual tests.

Nonparametric Rank Test

Traditional nonparametric tests, such as the signed rank and sign tests, assume that the Central Limit Theorem (CLT) holds and that the analyzed sample is large enough for the CLT to be applied. Corrado (1989) developed a nonparametric rank test which is correctly specified independent of the degree of skewness in the cross-sectional

distribution of abnormal returns. Further, this nonparametric rank test is found to be less affected by event-induced variance.

Several additional methods were considered, but are not used in this analysis. Generalized least squares (GLS) is useful in the presence of serial correlation and heteroskedasticity, but it is often infeasible in practice[9]. Froot's (1989) version of the method-of-moments technique requires samples to be segregated by industry. This, coupled with previous findings of ineffectiveness warrants its exclusion from this study. The test statistics for all of the proposed methodologies are given in the appendix.

RESULTS

Before the effect of event-induced variance can be examined, we have to observe the ability of various abnormal return detection methods when conditions are stable. The first section of Table 1 shows the average rejection rates for various abnormal return detection methods when no event-induced variance and no abnormal returns are present. The simulations performed here are conducted under the same conditions as in Brown and Warner (1985).

TABLE 1
Average rejection rates for various abnormal return detection methods where no event induced variance is present, and with abnormal returns(ì) of 0%, 1%, and 2%. All rejection rates are from 250 portfolios each containing 50 securities from July 1962 through December 1995 and test the null hypothesis that the average abnormal return is zero.

	One-tailed tests			Two-tailed tests	
	á=.05	á=.01		á=.05	á=.01
ì = 0%					
Market Model Residual	.068	.028		.072	.028
Standardized Residual	.064	.024		.068	.032
Cross-Sectional	.056	.012		.060	.020
Standardized Cross-Sectional	.052	.012		.056	.016
Sign	.032	.006		.040	.012
Nonparametric Rank	.060	.018		.068	.028
ì = 1%					
Market Model Residual	.848	.564		.772	.712
Standardized Residual	.932	.680		.908	.844
Cross-Sectional	.872	.608		.796	.728
Standardized Cross-Sectional	.968	.892		.952	.884
Sign	.780	.508		.684	.612
Nonparametric Rank	.956	.852		.940	.876
ì = 2%					
Market Model Residual	1.000	.996		1.000	.996
Standardized Residual	1.000	1.000		1.000	1.000
Cross-Sectional	.996	.996		.996	.992
Standardized Cross-Sectional	1.000	1.000		1.000	1.000
Sign	.972	.948		.952	.940
Nonparametric Rank	1.000	1.000		1.000	1.000

Given an alpha value of .05, we would expect the average rejection rate to be close to 5%, while the average rejection rate for an alpha of .01 would be near 1%. All six of the performance measures appear to be well specified under these simplified conditions. These results are consistent with the two comparable cases in Brown and Warner's (1985) simulation.

When abnormal returns are artificially introduced (ì=1 and ì=2), the average rejection rates for all methods respond by increasing to values nearer to one. There is no statistical procedure available to determine a significant cutoff for detection ability. However, when abnormal returns are present, the higher the rejection rate, the better. For example, the basic market model rejects the null 84.8% of the time when abnormal returns equal 1% and no event-induced variance is present. Hence, 15.2% of the time, the researcher will be erroneously led to believe that no abnormal returns are present[10]. For the Standardized cross-sectional method under the same conditions, the correct conclusion will be reached 96.8% of the time. Clearly, a higher null rejection rate is better when abnormal returns are in fact present.

When abnormal returns are equal to 2%, all six methods perform relatively well. The only method that yields mild, yet consistently lower than desired rejection rates is the sign method. Since this method is traditionally used in conjunction with other methods, this result is not that disturbing. To sum, in the absence of event-induced variance, even the most basic event study methodologies perform relatively well and any effort to use more advanced techniques yields only slight improvements.

TABLE 2
Average rejection rates for various abnormal return detection methods for 250 portfolios of 50 securities where no abnormal returns are present, and with event-induced variance(k) of 0.5, 1, and 2. The null hypothesis is that the average abnormal return is zero. Abnormal Performance is a random variable drawn from $N(0,k\ddot{u}^2)$, where k is a constant and $\ddot{u}^2$ is either the individual-security or the average estimation-period variance.

	Panel A				Panel B			
	Event-induced variance proportional to individual security estimation period variance				*Event-induced variance proportional to average estimation period variance*			
	One-tailed		Two-tailed		One-tailed		Two-tailed	
	á=.05	á=.01	á=.05	á=.01	á=.05	á=.01	á=.05	á=.01
k = 0.5								
Market Model Residual	.116	.044	.148	.060	.128	.056	.132	.060
Standardized Residual	.124	.048	.152	.068	.132	.060	.136	.064
Cross-Sectional	.072	.020	.096	.024	.072	.020	.068	.020
Standardized Cross-Sectional	.064	.016	.092	.020	.064	.016	.064	.016
Sign	.080	.028	.108	.028	.080	.032	.092	.036
Nonparametric Rank	.048	.008	.076	.012	.048	.008	.048	.012
k = 1								
Market Model Residual	.132	.068	.196	.068	.152	.064	.160	.076
Standardized Residual	.136	.072	.208	.072	.160	.068	.164	.084
Cross-Sectional	.072	.024	.108	.028	.076	.024	.068	.020
Standardized Cross-Sectional	.060	.016	.100	.024	.068	.020	.068	.016
Sign	.076	.028	.116	.036	.084	.036	.108	.044
Nonparametric Rank	.060	.012	.084	.016	.052	.012	.060	.016
k = 2								
Market Model Residual	.188	.108	.248	.120	.256	.088	.268	.104
Standardized Residual	.196	.120	.260	.072	.268	.104	.284	.112
Cross-Sectional	.076	.024	.088	.032	.080	.028	.088	.028
Standardized Cross-Sectional	.064	.020	.076	.028	.080	.024	.084	.024
Sign	.088	.036	.124	.044	.144	.052	.156	.080
Nonparametric Rank	.060	.016	.072	.020	.068	.020	.080	.020

Table 2 shows the average rejection rates for various abnormal return detection methods where no abnormal returns are present, but varying levels of event-induced variance are present. More specifically, Panel A reports null

rejection rates when event-induced variance is assumed to be a multiple of the individual security's estimation-period residual variance, while Panel B reports null rejection rates when event-induced variance is assumed to be a multiple of the average of the portfolio's estimation-period residual variance. From the first section of Table 2 (k=0.5), we see that even a slight amount of event-induced variance causes the Market Model Residual and the Standardized Residual methods to fail. For example, the Market Model Residual rejection rate in Panel A's two-tail test where alpha equals .05 shows a rejection rate of 14.8% which represents a substantial increase over the more accurate 7.2% rejection rate in the absence of induced variance (from Table 1). The Standardized Residual method's rejection rate also increased from 6.8% to 15.2% in the wake of mild event-induced variance. The Standardized Cross-Sectional and Nonparametric Rank methods performed well, while the Cross-Sectional and Sign methods performed only slightly worse.

When k=1, the Market Model Residual and Standardized Residual continue to deteriorate and claim to detect abnormal performance 19.6% and 20.8% of the time, respectively, when only 5% would be anticipated. The detection rates climb to 24.8% and 26.0%, respectively, when event-induced variance is increased to k=2. The other methods also erroneously yield higher rejection rates, but the increases are less dramatic. The Standardized Cross-Sectional and Nonparametric Rank tests perform the best and are relatively unaffected, while the Sign, and to a lesser extent, the Cross-Sectional methods, lose reliability.

TABLE 3

Average rejection rates for various abnormal return detection methods for 250 portfolios of 50 securities where abnormal returns are fixed at 1%, and with event-induced variance(k) of 0.5, 1, and 2. The null hypothesis is that the average abnormal return is zero. Abnormal Performance is a random variable drawn from $N(1, k\ddot{u}^2)$, where k is a constant and $\ddot{u}^2$ is either the individual-security or the average estimation-period variance.

	Panel A					Panel B			
	Event-induced variance proportional to individual security estimation period variance					*Event-induced variance proportional to average estimation period variance*			
	One-tailed		Two-tailed			One-tailed		Two-tailed	
	á=.05	á=.01	á=.05	á=.01		á=.05	á=.01	á=.05	á=.01
					k = 0.5				
Market Model Residual	.824	.604	.788	.596		.812	.592	.796	.580
Standardized Residual	.912	.836	.884	.812		.900	.824	.892	.812
Cross-Sectional	.660	.412	.556	.392		.644	.400	.628	.384
Standardized Cross-Sectional	.904	.816	.876	.796		.896	.812	.884	.804
Sign	.728	.584	.616	.420		.720	.572	.704	.552
Nonparametric Rank	.920	.872	.892	.860		.912	.860	.900	.844
					k = 1				
Market Model Residual	.804	.596	.760	.572		.788	.592	.708	.524
Standardized Residual	.888	.780	.824	.744		.868	.764	.792	.724
Cross-Sectional	.632	.396	.564	.396		.620	.380	.584	.356
Standardized Cross-Sectional	.864	.640	.832	.728		.876	.752	.856	.760
Sign	.672	.428	.616	.420		.660	.412	.580	.400
Nonparametric Rank	.876	.660	.852	.748		.876	.760	.860	.736
					k = 2				
Market Model Residual	.740	.592	.740	.556		.728	.576	.680	.540
Standardized Residual	.812	.600	.756	.568		.804	.636	.772	.616
Cross-Sectional	.596	.384	.548	.380		.584	.372	.560	.344
Standardized Cross-Sectional	.848	.632	.824	.748		.848	.732	.840	.728
Sign	.648	.404	.604	.408		.632	.404	.564	.396
Nonparametric Rank	.860	.652	.840	.732		.852	.748	.852	.732

Table 3 is similar in all aspects to Table 2 except that it reports average rejection rates where abnormal returns are fixed at 1%. Levels of event-induced variance are again allowed to vary from 0.5, 1, and 2. The results indicate very much the same information as did the previous table. The Nonparametric Rank test provides the highest, and therefore, most accurate rejection rates followed by the still reliable Standardized Cross-Sectional method. The Sign and the Cross-Sectional methods have actually become less effective than both the Market Model Residual and the Standardized Residual methods. These results are consistent across all three levels of event-induced variance.

TABLE 4
Average rejection rates for various abnormal return detection methods for 250 portfolios of 50 securities where abnormal returns are fixed at 2%, and with event-induced variance(k) of 0.5, 1, and 2. The null hypothesis is that the average abnormal return is zero. Abnormal Performance is a random variable drawn from $N(2,k\ddot{u}^2)$, where k is a constant and $\ddot{u}^2$ is either the individual-security or the average estimation-period variance.

	Panel A					Panel B			
	Event-induced variance proportional to individual security estimation period variance					*Event-induced variance proportional to average estimation period variance*			
	One-tailed		Two-tailed			One-tailed		Two-tailed	
	á=.05	á=.01	á=.05	á=.01		á=.05	á=.01	á=.05	á=.01
					k = 0.5				
Market Model Residual	.996	.987	.992	.984		.996	.988	.996	.988
Standardized Residual	.996	.996	.996	.996		.996	.992	.992	.988
Cross-Sectional	.992	.988	.988	.984		.992	.988	.988	.984
Standardized Cross-Sectional	1.000	1.000	1.000	1.000		1.000	1.000	1.000	1.000
Sign	.984	.976	.976	.972		.988	.976	.972	.964
Nonparametric Rank	1.000	1.000	1.000	1.000		1.000	.996	.996	.996
					k = 1				
Market Model Residual	.988	.980	.984	.976		.984	.976	.984	.976
Standardized Residual	.992	.984	.984	.980		.992	.984	.988	.980
Cross-Sectional	.992	.988	.988	.980		.988	.984	.988	.984
Standardized Cross-Sectional	1.000	1.000	1.000	.996		.996	.996	.996	.996
Sign	.972	.968	.964	.952		.964	.960	.960	.956
Nonparametric Rank	.992	.988	.992	.984		.992	.988	.992	.984
					k = 2				
Market Model Residual	.972	.956	.964	.952		.960	.948	.960	.944
Standardized Residual	.960	.944	.952	.936		.956	.940	.964	.948
Cross-Sectional	.976	.960	.972	.956		.980	.964	.976	.960
Standardized Cross-Sectional	.992	.984	.984	.980		.988	.980	.988	.976
Sign	.932	.912	.920	.904		.920	.904	.920	.896
Nonparametric Rank	.980	.964	.968	.948		.980	.964	.984	.968

Table 4 is similar in all aspects to Tables 2 and 3 except that it reports average rejection rates where abnormal returns are fixed at 2%. Levels of event-induced variance are again allowed to vary from 0.5, 1, and 2. The results show the Sign test rejects the null with the least frequency indicating that it is less effective at correctly identifying abnormal returns. The Cross-Sectional method has rebounded to show slight preference over both the Market Model Residual and the Standardized Residual, while the Standardized Cross-Sectional method appears to have emerged over the Nonparametric test as the leader in ability to correctly identify significant abnormal returns.

CONCLUSIONS

Event-induced variance is widely observed in event studies, yet it is often ignored from a methodological standpoint. We show that the most commonly used methods in event studies have a high failure rate in the presence of even slight event-induced variance. To overcome the event-induced variance problem, six methods are tested in a manner similar to Brown and Warner(1985) and in accordance with Boehmer, et. al. The Nonparametric Rank and Standardized Cross-Sectional methods consistently outperform the other four procedures and are relatively free from event-induced variance bias. We also provide tables containing various combinations of sample characteristics that future event study researchers can match against their own samples to determine which statistical test is the most appropriate for their specific situation.

ENDNOTES

1. Event-induced variance is actually when the variance over the estimation period is different from the variance over the event window. Since event period variance is usually higher, we will adapt the definition as such.

2. For example, firms with a high percentage of insider ownership versus an atomistic firm should be affected very differently when confronted by a takeover attempt.

3. Masulis(1980) was the first to propose the Mean Adjusted Returns benchmark. Cowles(1933) and Latane and James(1979) used the Market Adjusted Returns approach. Brown and Warner(1980) provide a detailed description of these various procedures (pp. 207-211 and 250-255).

4. This is especially true under less restrictive conditions such as no event-date clustering, no event-induced variance, and the correct and accurate identification of the event date.

5. Several variations of the risk adjusted approach exist. For example, the own variance model, the multiple-index model, and the zero beta or Fama-MacBeth(1973) model which is based on the Black(1972) form of CAPM. The single index market model (SIMM) is chosen based on Brenner(1979), which concludes that it performs as well as more advanced techniques.

6. This is because when a model correctly considers the ex post relationship between a security's generated expected return and its true expected return, the variance of the event will be lower.

7. Using a constant allows for upward mean shifts in returns without an increase in conditional variance. Thus, an event date can be analyzed in isolation without higher-order moments being affected as well.

8. The observed variance over the event window could be used instead, but since the event dates are selected at random, there is no reason to believe that one period would provide better results than another.

9. GLS is especially impractical with large data sets such as this one. For further details see Collins, Rozeff, and Salatka(1982), Collins and Dent(1984), and Thompson(1985).

10. To be technically and statistically correct, this is simply interpreted as the researcher not being able to say that there exists abnormal returns.

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APPENDIX

All of the following test statistics assume that the null distribution is normal with a mean of zero and a variance of one.

1. Market model Residual: equals the sum of the event-period abnormal returns divided by the square root of the sum of all securities' estimation-period residual variances.

$$\frac{\dfrac{1}{N}\sum_{i=1}^{N} A_{iE}}{\dfrac{1}{N}\sqrt{\sum_{i=1}^{N}\dfrac{1}{T-1}\sum_{t=1}^{T}(A_{it} - \sum_{t=1}^{T}\dfrac{A_{it}}{T})^2}}$$

2. Standardized Residual: equals the sum of the residuals standardized by their standard deviations divided by the (approximate) square root of the number of sample firms.

$$\frac{\sum_{i=1}^{N} SR_{iE}}{\sqrt{\sum_{i=1}^{N}\dfrac{T_i-2}{T_i-4}}}$$

3. Cross-Sectional: divides the average event-period residual by its contemporaneous cross-sectional standard error.

$$\frac{\dfrac{1}{N}\sum_{i=1}^{N} A_{iE}}{\sqrt{\dfrac{1}{N(N-1)}\sum_{i=1}^{N}(A_{iE} - \sum_{i=1}^{N}\dfrac{A_{iE}}{N})^2}}$$

4. Standardized Cross-Sectional: The residuals are standardized by their standard deviations. Then the average event-period standardized residual is divided by its contemporaneous cross-sectional error.

$$\frac{\dfrac{1}{N}\sum_{i=1}^{N} SR_{iE}}{\sqrt{\dfrac{1}{N(N-1)}\sum_{i=1}^{N}(SR_{iE} - \sum_{i=1}^{N}\dfrac{SR_{iE}}{N})^2}}$$

5. Sign: the observed proportion of positive returns minus 0.50 divided by the standard deviation of a binomial distribution. The two-sided test statistic equals

$$|P - \frac{1}{2}|[\frac{(\frac{1}{2})^2}{N}]^{-1/2}$$

The one-sided test statistic is given by:

$$p - \frac{1}{2}|\frac{(\frac{1}{-})^2}{N}~^{-1/2}$$

6. Nonparametric Rank:

$$\frac{\frac{1}{N}\sum_{i=1}^{N}(K_{i0}-\frac{1}{2})}{}$$

where,

$$S(K)=\sqrt{\frac{1}{T}\sum(\frac{1}{N}(K_{it}-\frac{t}{2}))}$$

For all of the above test statistics, we use the following notation:

N
T   = number of days in security i's estimation period,
A_{it} = security i's abnormal return on day t,
A_{iE} = security i's abnormal return on the event day,
R_m = average market return during the estimation period,
R_{mt}
S
P   = the frequency of positive residuals,
K_{it} = the rank of the excess return A_{it}
S(K) = standard deviation,
A_{iE}

$$SR_{iE}=\frac{A_{iE}}{\hat{s}_i\sqrt{1+\frac{1}{T_i}+\frac{(R_{mE}-\overline{R}_m)^2}{\sum_{t=1}^{T_t}(R_{mt}-\overline{R}_m)^2}}}$$