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Parametric and Nonparametric Event Study Tests: A Review

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Abstract

This paper presents a modest attempt to review the existing methodologies for measuring short-run abnormal performance of firms following certain corporate events. In doing so, the study discusses different parametric as well as nonparametric testing procedures available in the literature. Reviewing the prior literature reveals that the nonparametric sign and rank tests are better specified than parametric procedures. However, in case of detecting the short-run anomalies, we document that nonparametric tests have higher power relative to standard parametric approaches.

Keywords: event study, short-run anomalies, sign test, rank test

1. Introduction

An event study is an empirical procedure that measures the effect of new information on the price of an asset, i.e. an event study is concerned with the impact of an event on the market prices of a company's publicly traded securities. In particular, researchers are concerned with the hypothesis that an event will have impact on the value of a firm or firms, and that this impact will be reflected on the stock and other security prices, manifesting itself in abnormal security returns. For instance, an event study might be conducted for the purpose of determining the impact of corporate earnings announcements on the stock price of the company.

The event study methodology is widely used in finance, accounting and economics. Many types of events are studied with event studies. Such events may include takeover announcements, environmental regulation enactments, patent filing announcements, competitor bankruptcy announcements, CEO resignation announcements, etc. Event studies are employed to measure market efficiency and to determine the impact of a given event on security prices. Such methodology refers to the set of econometric techniques used to measure and interpret the effects of an event on the value of a firm.

It is a difficult task to determine how many event studies have been published so far. Kothari and Warner (2007), for example, report that the number of published papers that deal with the event study methodology easily exceeds 500 and continues to grow. Although there have been many advances in this methodology over the years, the core elements of a typical event study can be found in two landmark papers by Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969) (henceforth FFJR).

The prime objective of this paper is to highlight the important parametric and nonparametric tests used in short-run event study methodology. To serve this purpose, we first review the existing literature of short-run event studies and then try to compare standard parametric tests with different nonparametric approaches available in the literature. Reviewing a large number of elementary studies suggests that the nonparametric sign and rank tests provide better specification and power than standard parametric approaches in detecting the abnormal performance.

The rest of the paper is organized as follows: Section 2 reviews the existing literature and reports the significant developments in the event study methodology. Parametric as well as nonparametric event study tests are discussed in Section 3. Section 4 outlines some recent developments in nonparametric approaches. Section 5 concludes.

2. Literature Review

Although the core elements of a typical event study are extensively summarized by Ball and Brown (1968) and FFJR, these papers are not the first that portray event studies. MacKinlay (1997) reports an early event study by Dolley (1933) which examines the stock price reaction to stock splits by studying nominal price changes at the time of the split. Using a sample of 95 splits from 1921 to 1931, Dolley finds that the price increased in 57 of the cases and the price declined in only 26 instances.

In the late 1960s, Ball and Brown (1968) and FFJR introduced the methodology that is essentially equivalent to that which is in use today. Ball and Brown (1968) conclude that annual accounting income data contains information that is related to stock prices. They found that income forecast errors, which are measured by the difference between announced and expected accounting earnings, have a positive impact on the abnormal performance index around the annual report announcement date.

FFJR also note that stock prices appear to adjust to new information. Stock splits generally occur following periods when stock prices significantly increase relative to the market. They found that, after a split announcement, stock prices seem to quickly reflect all available information and do not generate any abnormal returns. The results demonstrate the efficiency of the capital market.

Since these pioneering studies, numerous modifications have been developed in order to investigate the impact of a number of potential problems of concern in the literature which include non-normality of returns and excess returns, bias in OLS estimates of market model parameters in the presence of non-synchronous trading and estimation of the variance to be used in hypothesis tests concerning the mean excess return. Brown and Warner (1980, 1985) deal with the practical importance of these complications. In the 1980 paper, they consider implementation issues for data sampled at a monthly interval, while the 1985 paper deals with issues for daily data.

However, the issue of event-induced volatility has been a source of concern in the literature for some time. Brown and Warner (1980, 1985) report that increases in variance may result in misspecification of the traditional test statistics and that the power of tests can be improved by appropriately modeling the volatility process. Other studies such as Aktas et al. (2007), Harrington and Shrider (2007) and Higgins and Peterson (1998) also document that all events induce an increase in cross-sectional variance that must be estimated and adjustments embodied in all tests used to assess the statistical significance of event date abnormal returns. Boehmer, Musumeci, and Poulsen (BMP) (1991) argue that the event-period returns should be standardized by the estimation-period standard deviation, and the cross-sectional mean of the standardized returns needs to be divided by their cross-sectional standard deviation to yield the test statistic. BMP approach implicitly assumes that the event-induced variance is the same for all securities in the sample. Corrado (1989) introduces the nonparametric rank test to deal with the issue of event-induced variance. Simulations show higher power of the rank test relative to the traditional tests. Simulations in BMP approach also confirm the same.

In traditional event study methodology, however, it is assumed that the abnormal returns are cross-sectionally uncorrelated. This assumption is valid when the event day is not common to the firms. Brown and Warner (1980, 1985) show that even when the event day is common for the firms which are not from the same industry, use of the market model to derive the abnormal return reduces the inter-correlations virtually to zero. But, if the firms are from the same industry, extracting market factor may not reduce the cross-sectional residual correlation. Consequently, using the traditional standardized return test statistics, even moderate cross-sectional correlation in an event study causes substantial over-rejection of the null hypothesis of no abnormal performance. Kolari and Pynnönen (2010) propose simple corrections to the popular Patell (1976) and Boehmer, Musumeci, and Poulsen (1991) statistics to account for the correlation. They show that, when there is no event-induced volatility increase, each of these corrected test statistics is approximately equally powerful and rejects the null hypothesis of no abnormal performance at the correct nominal rate when it is true.

3. Event Study Tests

A number of event studies rely on parametric test statistics. But, one disadvantage of using parametric test statistics is that they do require essential assumptions about the probability distribution of returns. Brown and Warner (1985) report that stock prices are not normally distributed. Consequently, when this assumption of normality is violated, parametric tests yield misspecified test statistics.

Non-parametric tests, on the other hand, are well-specified and more powerful at detecting a false null hypothesis of no abnormal returns. The most successful among these tests were the nonparametric sign and rank tests advanced in Corrado (1989), Zivney and Thompson (1989), and Corrado and Zivney (1992). Well-known studies of this type are Cowan (1992), Campbell and Wasley (1993, 1996), and Corrado and Truong (2008). Each of these studies documents that sign and rank tests provide better specification and power than parametric tests.

In this section, we review different types of nonparametric event study tests available in the literature. In doing so, we first discuss standard parametric procedures for testing the null of no abnormal performance. Reviewing nonparametric tests will follow.

3.1 T-Test-Mean Excess Returns

Let ε_{it} denote the abnormal return of security *i* on day *t*, i.e., $\varepsilon_{it} = R_{it} - E(R_{it})$, where R_{it} represents the return of security *i* on day *t* and $E(R_{it})$ indicates the expected return generated by a particular benchmark model. Also let *t=0* be the event date. Now for each day *t*, the cross-sectional average excess return of *N* securities is calculated as:

$$\overline{\varepsilon_t} = \frac{1}{N}\sum_{i=1}^{N} \varepsilon_{it}$$

The day 0 test statistic is then given by:

$$J_1 = \frac{\overline{\varepsilon_0}}{S(\bar{\varepsilon})}$$

with $S(\bar{\varepsilon})$ being an estimate of standard deviation of the average abnormal returns.

3.2 T-Test-Mean Standardized Excess Returns

In this case, each ε_{it} is divided by its estimated standard deviation to produce a standardized excess return computed as:

$$\varepsilon'_{it} = \frac{\varepsilon_{it}}{S(\varepsilon_i)}$$

Then the day 0 test statistic is defined as:

$$J_2 = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \varepsilon'_{it}$$

3.3 Cross-Sectional Dependence (Crude Adjustment)

Brown and Warner (1980) suggest a crude dependence adjustment for cross sectional dependence. The variance of the average abnormal return of the event day is estimated using the time series variance of the average of the abnormal returns.

In this case, the day 0 test statistic is given by:

$$J_3 = \frac{\overline{\varepsilon_0}}{\sqrt{\widetilde{\sigma^2}}}$$

Here, $\widetilde{\sigma^2} = \frac{1}{T-1}\sum_{t=1}^{T}(\overline{\varepsilon_t} - \bar{\varepsilon})^2$ and $\bar{\varepsilon} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\varepsilon_{it}$

3.4 Generalized Sign Test

The sign test, often used in event studies, refers to a simple binomial test of whether the frequency of positive abnormal residuals equals 50 percent. Brown and Warner (1980) point out that correct specification of the sign test requires equal numbers of positive and negative abnormal returns, absent a reaction to an event. Cowan, Nayar and Singh (1990) and Sanger and Peterson (1990), use a refined version of this sign test by allowing the null hypothesis to be different from 0.5 and this modified approach is called generalized sign test.

In order to implement this test, we first need to determine the proportion of securities in the sample having non-negative abnormal returns under the null hypothesis of no abnormal performance. The value for the null is estimated as the average fraction of stocks with non-negative abnormal returns in the estimation period. If abnormal returns are independent across stocks, under the null hypothesis the number of non-negative values of abnormal returns has a binomial distribution with parameter p.

The statistic for the generalized sign test is defined as:

$$z = \frac{|p_0 - p|}{\sqrt{p(1-p)N}}$$

where p_0 denotes the observed fraction of positive returns computed across stocks in one particular event week, or the average fraction of firms with non-negative abnormal returns for events occurring over multiple weeks. This statistic is approximately distributed as normal distribution with zero mean and variance 1.

The advantage of the generalized sign test is that it takes into account the evidence of skewness in security returns. However, the power and specification of the generalized sign test have not been documented.

3.5 Wilcoxon Signed-Rank Test

Employing Wilcoxon signed-rank test is handy, since it considers that both the sign and the magnitude of abnormal returns are significant. The test statistic in this case is given by:

$$W = \sum_{i=1}^{N} r_i^+$$

Where r_i^+ is the positive rank of the absolute value of abnormal returns. This test assumes that none of the absolute values are equal, and that each is a nonzero value. Under the null hypothesis of equally likely positive or negative abnormal returns and when *N* is large, *W* asymptotically follows a normal distribution with the following mean and variance:

$$E(W) = \frac{N(N+1)}{4}$$

$$V(W) = \frac{N(N+1)(2N+1)}{12}$$

3.6 Corrado's Rank Test

Corrado (1989) observes that another nonparametric test, known as the rank test, is more powerful than the standard parametric tests. Like the generalized sign test, the rank test does not require symmetry of the cross-sectional abnormal return distribution.

In order to implement this test, it is first necessary to transform each firm's abnormal returns into their respective ranks. To do so, let K_{it} denote the rank of the abnormal return ε_{it} in security *i*'s time series of T excess returns, i.e., $K_{it} = rank(\varepsilon_{it})$; t=1, 2,…, T. Here $\varepsilon_{it} \geq \varepsilon_{ij}$ means $K_{it} \geq K_{ij}$ and $T \geq K_{it} \geq 1$. The average rank is then calculated as $\bar{K} = \frac{T+1}{2}$ and the day 0 test statistic is given by

$$R = \frac{\frac{1}{N}\sum_{I=1}^{N}(K_{i0} - \bar{K})}{S(K)}$$

where the standard deviation S(K) is computed as:

$$S(K) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left[\sum_{i=1}^{N}(K_{it} - \bar{K})/N\right]^2}$$

This statistic is distributed asymptotically as unit normal. Cowan and Sergeant (1996) document that if the return variance is unlikely to increase, then Corrado's rank test is better specified and more powerful than parametric tests. With the increase in variance, however, this test is misspecified.

Table 1 presents parametric and nonparametric event study tests reviewed in this paper. Each of these approaches is employed to investigate the short-run abnormal performance of firms following major corporate events.

Table 1. Summary of alternative methodologies

Methods	Test Statistics
t-test-mean excess returns	$J_1 = \frac{\overline{\varepsilon_0}}{S(\varepsilon)}$
t-test-mean standardized excess returns	$J_2 = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \varepsilon'_{it}$
Cross-Sectional Dependence (Crude Adjustment)	$J_3 = \frac{\overline{\varepsilon_0}}{\sqrt{\widehat{\sigma^2}}}$
Generalized Sign Test	$z = \frac{\lvert p_0 - p \rvert}{\sqrt{p(1-p)N}}$
Wilcoxon Signed-Rank Test	$W = \sum_{i=1}^{N} r_i^{+}$
Corrado's Rank Test	$R = \frac{\frac{1}{N}\sum_{i=1}^{N}(K_{i0} - \bar{K})}{S(K)}$

Note. This table summarizes the test statistics of different empirical procedures discussed in this study. The first three methodologies refer to parametric event study approaches and the rest indicate nonparametric procedures.

4. Recent Developments in Non-parametric Event Study Tests

The rank tests, introduced by Corrado (1989) and Corrado and Zivney (1992), are applied for testing single day event abnormal returns. Corrado (1989), however, reports that implementing rank test for CARs requires defining multiple-day returns that match the number of days in the CARs. This can be done by dividing the estimation period and event period into intervals matching the number of days in the CAR. Unfortunately, this procedure is not very effective, because the number of observations quickly becomes impracticably small as the CAR-period lengthens and the resultant loss of observations weakens the abnormal return model estimation. Cowan (1992) and Campbell and Wasley (1993) conduct Corrado's rank test for testing cumulative abnormal returns by simply accumulating daily ranks of abnormal returns within the CAR-period. Like the multi-day approach, cumulated ranks approach also has potential shortcomings. Cowan (1992) and Kolari and Pynnönen (2010) report that such procedure quickly loses power in detecting abnormal returns, especially in longer event windows. Because this approach involves transferring the returns to rank numbers and hence the returns no longer capture the magnitudes of returns, only their relative ranks. Thus, if one large return is randomly assigned to one day within the event window independently for each stock, there is only one potentially outstanding rank for each stock that is randomly scattered across the window. This is likely to average largely out in the cumulative rank sum resulting in poor power properties of the test.

In order to overcome these puzzles, Kolari and Pynnönen (2011) introduce a generalized rank test based on generalized standardized abnormal returns which can be applied for testing both single abnormal returns and cumulative abnormal returns. The proposed test is robust to abnormal return serial correlation, event-induced volatility and cross-sectional correlation of abnormal returns due to event day clustering. Further details can be found in Kolari and Pynnönen (2011).

5. Conclusions

Event studies are conducted for the purpose of investigating the effect of an event on stock returns. Typical events include firm-specific events and Economy-wide events. Firm-specific events usually indicate a change in the company policy. Examples of such events involve earnings, investment, mergers and acquisitions, issues of new debt or equity, stock splits, etc. announcements. Economy-wide events, on the other hand, are employed in large sample event studies which investigate the impact of a particular event on relevant securities. This type of events includes inflation, interest rate, consumer confidence, trade deficient, etc. announcements.

This paper presents a modest attempt to portray the short-run event study methodology beginning with FFJR in the late 1960s. The main objective of this article is to outline the existing parametric and nonparametric tests used in short-run event studies. To serve this purpose, standard parametric tests, Generalized Sign Test, Wilcoxon Signed-Rank Test and Corrado's Rank Test are discussed. Recent developments in non-parametric event study tests are also reviewed. For example, Kolari and Pynnönen (2011) recently introduce a generalized rank test based on generalized standardized abnormal returns which is used to test both single abnormal returns and cumulative abnormal returns. Reviewing the prior studies concludes that nonparametric sign and rank tests are well specified and have more power than the standard parametric approaches in detecting the short-run anomalies.

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