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A Complete Nonparametric Event Study Approach

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Abstract. Event studies have been used to examine the direction, magnitude, and speed of security price reactions to various phenomenon. Concerns over the lack of normality in stock return distributions motivated the introduction of nonparametric test statistics in the event study literature. A parametric procedure (OLS), however, has been extensively employed in the estimation of parameters for the market model. This paper, in contrast, applies Theil's nonparametric regression in the estimation of abnormal returns; an approach which is distribution free and provides a complete nonparametric approach for the detection of abnormal performance.

Simulation results indicate Theil's estimation procedure offers a slight improvement in power in the detection of abnormal performance over the traditionally employed methodology. The results suggest employing Theil's nonparametric estimation procedure combined with the rank statistic. This complete nonparametric combination offers similar power with fewer underlying assumptions.

Key words: nonparametric, event study, methodology

1. Introduction

Researchers in various fields are interested in how new information affects stock prices. Since the seminal article of Fama et al. (1969), event studies have been frequently employed to investigate if new information imparts a change in equity value. Applications of event studies are numerous and include governmental actions, capital budgeting decisions, acquisitions and mergers, and changes in management.

Crucial to all event studies is the ability to accurately detect abnormal performance. In two widely cited papers in finance, Brown and Warner (1980; 1985) examine the ability of various event study methodologies to appropriately detect abnormal performance. Using stock returns from the NYSE and AMEX, the authors find that event studies based on the ordinary least squares (OLS) estimation of the market model which use parametric tests are well specified under a variety of conditions. The wide acceptance of OLS estimation may be attributed to the ease of estimation, its underlying capital asset pricing theory, and that it provides the best unbiased estimator under the condition of normality.

Concerns over the lack of normality in stock return distributions motivated the introduction of nonparametric test statistics. The rank test (Corrado, 1989) and the generalized sign test (Cowan, 1992) have both been found to have higher power than traditional parametric tests in detecting abnormal price changes in NYSE stocks. Campbell and Wasley (1993) find NASDAQ return distributions depart from normality to a much greater extent than NYSE/AMEX returns and support the superiority of the nonparametric test statistics.

What has been overlooked in the literature, however, is the estimation of the market model itself. Estimation via OLS may have several desirable properties providing the underlying assumptions are true, but if the assumption of normality is not appropriate, then a more general class of non-linear estimators may be preferred.

Previous studies have supported the use of nonparametric test statistics due to the lack of normality in security returns while simultaneously using a parametric procedure in the estimation of parameters (Corrado, 1989; Cowan, 1992; Campbell and Wasley, 1993). This paper applies Theil's nonparametric regression technique in the estimation of abnormal returns. Use of the Theil approach is distribution free and offers a complete nonparametric approach for event studies. Simulation results indicate that the combination of the Theil estimation procedure and a nonparametric test statistic offers a slight improvement in power over existing approaches in the detection of abnormal performance while relaxing the necessary assumptions.

The remainder of this paper is organized as follows. Section 2 describes the return generating model and abnormal performance measurement. Section 3 discusses how the estimation procedures are affected by non-normality. Section 4 describes the experimental design and the fifth section presents the simulation results. Section 6 summarizes the findings and provides suggestions for future research.

2. *Measurement of abnormal performance*

The detection of abnormal performance requires a return generating model during the estimation period to predict "normal" performance in the event window. Central to all event studies is the determination of what constitutes an abnormal return. Regardless of the return generating model employed, the fundamental concept is that an abnormal return (AR_{it}) is the difference between an actual return (R_{it}) and an expected return ($E(R_{it})$):

$$AR_{it} = R_{it} - E(R_{it}) \tag{1}$$

with each return model providing its own expectation for returns.

The market model abnormal returns are based upon[1]

$$AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i RM_t) \tag{2}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are estimated parameters from the market model for security i and RM_t represents the market return for period t. OLS has traditionally been employed in the estimation of these parameters. The OLS estimator provides minimum variance among all unbiased estimators if security returns are normally distributed. Under conditions of non-normality, however, OLS is only the best linear unbiased estimator and other non-linear estimators may be preferred.

3. Non-normality and estimation

A. Effects in OLS estimation

The effects of non-normality in OLS estimation may be seen as follows. After sorting the pairs of returns (RM_t, R_t) in ascending order based on the values of RM_t, the ordered pairs (RM_i, R_i) can be used to calculate slope values for all pairs following

$$\beta_{ij} = \frac{R_i - R_j}{RM_i - RM_j}. \tag{3}$$

It is then straight forward to show that $\hat{\beta}$ is a weighted average of the individual slopes with weights

$$W_{ij} = (RM_i - RM_j)^2. \tag{4}$$

The weighted average terms for $\hat{\beta}$ can be presented in an upper triangular matrix as follows.[2]

$$\begin{matrix} \beta_{12}(RM_1 - RM_2)^2 & \beta_{13}(RM_1 - RM_3)^2 & & \beta_{1t}(RM_1 - RM_t)^2 \\ & \beta_{23}(RM_2 - RM_3)^2 & & \beta_{2t}(RM_2 - RM_t)^2 \\ & & & \vdots \\ & & & \beta_{t-1,t}(RM_{t-1} - RM_t)^2. \end{matrix} \tag{5}$$

The elements on the center diagonal will have relatively low weights in the estimation process. Elements in the upper right with large differences between market returns, in contrast, will receive larger weights in the estimation process. Any errors associated with these elements may allow the estimated coefficients to be unduly influenced.[3]

Robust statistics should be applied when uncertainty exists as to the true underlying distribution.[4] A good robust estimator is fairly efficient regardless of the true error function and only slightly inefficient versus least squares if the true error distribution is normally distributed.[5] Under non-normality, the performance of a robust estimator should be superior to OLS.

B. Theil's nonparametric alternative

Chan and Lakonishok (1992) demonstrate that robust estimation offers potential efficiency gains in the estimation of beta risk. Although there are numerous possible robust estimators (see Andrews et. al., 1972, for a review), we investigate a nonparametric estimator first suggested by Theil (1950) due to its high efficiency and simplicity in computation and implementation.[6] Hussain and Sprent (1983) find Theil estimators to be slightly inefficient to OLS under normality but markedly superior under alternative distributions with heavy tails. Talwar (1993) finds Theil estimators to perform better than OLS with various non-normal return distributions suggested in finance literature[7].

Theil's incomplete method is estimated for each firm as follows:[8]

(1) Sort the N data pairs of (RM_t, R_t) in ascending order of the RM_t.
(2) Separate the data pairs into two groups based upon the median. Ignore the median pair if t is odd.
(3) Calculate a slope parameter β for each of the N/2 data pairs in each group using:

$$\beta_{(j,j+\frac{N}{2})} = \frac{R_{(j+\frac{N}{2})} - R_j}{RM_{(j+\frac{N}{2})} - RM_j}. \tag{6}$$

$$\text{For } j = 1 \text{ to } \frac{N}{2}$$

(4) Sort the calculated slope parameters in ascending order.
(5) Set β equal to the median slope and calculate the values of $\hat{\alpha}_i$ for all data pairs.
(6) Set α_i equal to the median value of the $\hat{\alpha}_i$.

Outliers will fall at the beginning and/or end of the ranking process. Focusing on the median thereby removes the potential influence of outlier observations from unduly influencing parameter estimates.

4. *Experimental design*

Following Brown and Warner (1980 and 1985), we use a simulation approach to examine the power of alternative methods designed to detect abnormal performance. Unlike previous research, the focus of the current study is on the estimation of the market model. We simulate event study conditions by randomly selecting 250 samples of 10, 25, and 50 securities with replacement from the daily CRSP NASDAQ and NYSE/AMEX returns files.[9] Each selected security is required to have a minimum time series of 261 days through the period ending 12–31–91. The time series is then subsequently divided into an estimation period (days -250 through -11 and an event period (days -10 through $+10$) for all eligible "events". Each security was restricted to having a minimum of 40 non-missing returns during the estimation period and no missing returns during the event window.[10]

The statistical significance of a given event is evaluated through the calculation of test statistics. Results are provided for three commonly employed test statistics for each estimation procedure. The standardized test statistic (see Patell, 1976; Dodd and Warner, 1983) represents the parametric alternatives.[11] Right skewness and leptokurtosis persistent in stock returns often invalidate the normality assumption underlying parametric statistics. The generalized sign test (see Sanger and Peterson, 1990; Cowan, 1992) and the rank test (see Corrado, 1989) are the nonparametric tests examined.[12]

5. *Simulation results*

A. *Properties of abnormal performance measures for individual securities and portfolios*

A random sample of 12,500 individual securities was selected with replacement Abnormal performance was computed employing each OLS estimation and Theil estimation procedures in each market (NASDAQ and NY/AMEX). Summary statistics for individual stock daily abnormal returns for each estimation method are presented in Panel A of Table 1. Panel A shows all of the estimation methods provide a standard deviation of approximately 3 and 4% for the NYSE and NASDAQ markets respectively.[13]

Without any induced abnormal performance, mean abnormal returns should be close to zero. Table 1 shows the mean abnormal return is not significantly different than zero (0.000185) employing OLS. The Theil estimation procedure produces a positive (0.001234) mean abnormal return. In the next section, we discuss if this leads to a higher probability of incorrectly rejecting the null hypothesis of no abnormal performance (Type I error).

Similar to Cowan (1992) and Campbell and Wasley (1993), the daily abnormal returns of individual securities depart considerably from normality. Each of the two estimation methods examined produce daily abnormal returns of individual securities that exhibit skewness, kurtosis, and a Shapiro-Wilk normality test indicating a rejection of normality at the 1% significance level.

Individual securities were subsequently grouped into 250 portfolios of 10, 25, and 50 securities. Summary statistics were calculated for each of the portfolios and are presented in Panel B of Table 1. Portfolios of different sizes from each market based on either estimation procedure display varying degrees of non-normality with the exception of NYSE portfolios of size 50. Consistent with Campbell and Wasley (1993), the departures from normality are more pronounced in the NASDAQ market and in the smaller portfolios.

The portfolio results for mean abnormal returns presented in Panel B are similar to the results shown in Panel A. Portfolio mean returns based on the Theil methodology are greater than zero while portfolio mean returns based on OLS are not significantly different than zero. As may be expected from diversification benefits, the standard deviation computed for portfolio returns is lower than that reported for individual securities shown in Panel A.

B. *Properties and power of test statistics under the null hypothesis*

Absent any abnormal performance on day 0, well specified test statistics should conform to standard normal random variables. Results investigating a hypothesized event on day 0 using both estimation methods for various portfolio sizes, and test statistics are presented

Table 1. Summary statistics of abnormal performance for samples of 12,500 securities. Abnormal performance is computed using parametric (OLS) and nonparametric (THEIL) estimation techniques using return data from the NYSE/AMEX and NASDAQ markets. Tests for normality are based on Shapiro-Wilk tests

Panel A
NYSE/AMEX

Estimation Method	Mean	Standard Deviation	Skewness	Excess Kurtosis	Test for Normality
OLS	0.000185	0.0304	1.94	25.38	0.0001
THEIL	0.001234	0.0305	1.95	24.82	0.0001
NASDAQ					
OLS	0.000168	0.041685	2.061	32.878	0.0001
THEIL	0.001266	0.041694	2.039	32.572	0.0001

Summary statistics of abnormal performance. Results are based upon 250 random values for each portfolio size of 10, 25, and 50 securities. Abnormal performance is computed using parametric (OLS) and nonparametric (THEIL) estimation techniques using return data from the NYSE/AMEX and NASDAQ markets.

Panel B
NYSE/AMEX

Estimation Method	Portfolio Size	Mean[a]	Standard Deviation	Skewness	Excess Kurtosis	Test for Normality
OLS	50	0.0002	0.0040	0.258	0.426	0.7914
	25	0.0005	0.0064	0.747	2.488	0.1121
	10	0.0000	0.0096	0.015	3.224	0.0881
THEIL	50	0.0012	0.0041	0.244	0.282	0.7315
	25	0.0015	0.0065	0.744	2.351	0.0576
	10	0.0010	0.0097	0.031	3.569	0.0217
NASDAQ						
OLS	50	0.0002	0.0057	0.632	0.703	0.0716
	25	0.0002	0.0077	0.733	1.432	0.0003
	10	0.0003	0.0126	0.590	2.368	0.0602
THEIL	50	0.0011	0.0056	0.581	0.825	0.0798
	25	0.0011	0.0076	0.702	1.492	0.0042
	10	0.0014	0.0127	0.570	2.258	0.0560

[a]No abnormal performance has been artificially introduced.

in Table 2 for NASDAQ portfolios.[14] The test statistics are generally well specified. The exception is the standardized test statistic estimated under the Theil estimation method which produces relatively higher estimated values.

The power of both estimation methods and test statistics to detect induced abnormal performance in portfolios of 50 securities is presented in Table 3 for NASDAQ firms.

Table 2. Summary statistics for the empirical distribution of test statistics for NASDAQ portfolio sizes of 10, 25, and 50 securities. The empirical distributions are based on 250 values of the test statistics for each portfolio size. Securities and event dates are randomly selected with replacement

NASDAQ

Portfolio Size	Estimation Method	Test Statistic	Mean[a]	Standard Deviation	*t*-Statistic	Skewness	Excess Kurtosis	Test for Normality
50	OLS	STD	0.042	1.114	0.603	0.087	0.274	0.7656
		Sign	−0.008	0.900	−0.148	−0.158	0.183	0.6760
		Rank	−0.005	0.986	−0.085	−0.161	0.246	0.9885
	THEIL	STD	0.276	1.089	4.004	0.126	0.306	0.8774
		Sign	0.052	0.945	0.866	0.076	−0.026	0.3272
		Rank	0.007	0.954	0.122	−0.096	−0.040	0.6940
25	OLS	STD	0.058	1.092	0.846	0.405	0.730	0.0814
		Sign	0.018	0.950	0.301	−0.215	0.229	0.9095
		Rank	0.015	0.960	0.242	−0.151	−0.035	0.5925
		STD	0.225	1.081	3.286	0.382	0.644	0.3189
		Sign	0.081	0.966	1.329	−0.119	0.079	0.9792
		Rank	0.034	0.979	0.550	−0.075	−0.174	0.5385
10	OLS	STD	0.033	1.120	0.431	1.031	4.319	0.0001
		Sign	0.031	0.967	0.511	0.046	−0.186	0.1215
		Rank	0.067	1.010	1.054	−0.104	−0.108	0.8364
	THEIL	STD	0.148	1.191	1.970	1.038	4.183	0.0001
		Sign	0.081	0.865	1.482	0.055	−0.156	0.3266
		Rank	0.039	1.002	0.616	−0.011	0.007	0.6058

[a]No abnormal performance has been artificially introduced.

Under the null hypothesis of zero abnormal performance, a well specified test statistic should have a Type I error rate close to a given significance (alpha) level. Tables 3 through 6 each present results for rejection rates based upon 1 and 5% significance levels for both lower and upper tail tests. Following Brown and Warner (1980; 1985), significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percentage of rejections falls between 2% and 8% (0% and 2.2%).[15]

The different estimation methods and test statistics are generally well specified in regards to both upper and lower tail tests for various portfolio sizes in each market. Consistent with the misspecification reported in Table 2 and the positive mean reported in Table 1, the standardized test statistic based on Theil estimation tends to over-reject in upper tail tests (this combination produces high Type I error). This combination appears to be well specified for lower tail tests, but the nonparametric alternatives provide more powerful tests as discussed below.

The results show that employing a complete nonparametric approach does not lead to over rejection of a valid null hypothesis of no abnormal performance. Tables 3 through 6 show that when no abnormal performance is induced (when the null hypothesis of zero should be true), the combination of employing the Theil estimation technique with nonparametric test statistics does not produce unacceptable Type I errors.

Table 3. A comparison of estimation methods for the market model of security returns in event studies. Numbers in the represent the percentage of 250 random samples of 50 NASDAQ securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0^c	0.25	0.5	1	1.5	0^c	0.25	0.5	1	1.5
OLS	STD	2.4	7.6	19.2	71.6	98.8	7.2	20	48	89.6	99.2
	Sign	0.8	34.8	85.2	99.2	100	3.6	79.6	98	99.6	100
	Rank	0.8	32.4	74.2	99.2	100	4.4	85.2	98	99.6	100
	STD	3.6	10.4	24	76.8	99.6	10.4	26.8	56	92.8	99.6
	Sign	0	100	100	100	100	6.4	100	100	100	100
	Rank	0.8	84.8	96	99.6	100	3.6	99.6	99.6	100	100

		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0^c	−0.25	−0.5	−1	−1.5	0^c	−0.25	−0.5	−1	−1.5
OLS	STD	0.4	5.6	19.6	68.8	95.6	5.6	20.4	43.2	88.8	98.4
	Sign	0	16.8	45.6	80.8	93.6	4.4	58.4	84.4	97.2	100
	Rank	0	36	72.4	97.2	100	5.2	86.4	98.4	100	100
Theil	STD	0	2.8	12.4	58.4	93.6	2.8	15.6	36.8	85.2	98
	Sign	0.4	3.2	4.4	19.6	38	3.6	12	20	39.2	58
	Rank	0	86.4	94.8	99.6	100	3.2	99.6	100	100	100

Notes: [a]The equally weighted NASDAQ market is used in the estimation. [b]The parametric standardized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.

Table 3 shows differences between the results based on OLS and Theil estimation procedures. The rank statistic based on Theil estimation of the market model exhibits slightly greater power in the detection of abnormal performance. The differences are most apparent at lower levels of induced abnormal performance. For example, when the rank statistic estimated under the Theil estimation procedure is used to detect a one-quarter percent induced abnormal return, the rank statistic rejects the null hypothesis of no abnormal performance about 85% of the time (at 1% significance level) versus 32% under OLS estimation.[16] The sign statistic based on the Theil methodology displays higher power in upper tail tests while the sign statistic produced by OLS is more powerful in lower tail tests. Hence, these results suggest that the complete nonparametric combination of the Theil estimation technique and the rank statistic provide well specified, relatively more powerful robust tests for event studies.

Table 1 showed the departures from normality were greatest for small NASDAQ portfolios. The results from inducing abnormal performance for NASDAQ portfolios of sizes 25 and 10 are presented in Tables 4 and 5 respectively. Similar to the results for larger portfolios, almost all statistics appear to be well specified under both OLS and Theil estimation. As shown before, the standardized test statistic based on Theil estimation tends to over-reject in upper tail tests.

Table 4 shows the sign statistic based on the Theil method provides nearly perfect detection of abnormal performance in upper tail tests but performs poorly in lower tail tests. This asymmetric difference in power is due to the different proportion of positive returns as

Table 4. A comparison of estimation methods for the market model of security returns in event studies. Numbers in the represent the percentage of 250 random samples of 25 NASDAQ securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	0.25	0.5	1	1.5	0[c]	0.25	0.5	1	1.5
OLS	STD	2.8	5.6	12.8	40.4	74.0	6.4	14.4	33.6	68.4	94.0
	Sign	0.8	19.2	50.0	78.4	92.0	4.0	58.0	87.2	98.0	99.6
	Rank	0.8	19.6	38.4	77.2	95.2	3.2	60.0	85.2	98.4	100.0
Theil	STD	4.8	7.6	15.2	46.0	79.2	8.0	20.0	37.6	73.6	94.8
	Sign	1.2	93.2	96.4	98.4	99.2	5.6	100.0	100.0	100.0	100.0
	Rank	1.2	58.0	66.8	86.0	97.6	3.2	91.2	95.6	99.6	100.0
		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	−0.25	−0.5	−1	−1.5	0[c]	−0.25	−0.5	−1	−1.5
OLS	STD	1.6	5.2	11.6	39.6	72.0	5.6	14.8	31.6	67.2	92.4
	Sign	0.8	8.4	20.0	41.2	62.8	4.4	34.0	58.0	80.8	91.6
	Rank	1.2	17.2	43.6	75.2	91.6	6.0	58.8	82.4	98.0	99.6
Theil	STD	0.4	3.6	7.6	31.2	66.0	4.0	10.8	24.8	64.0	89.6
	Sign	0.0	0.8	2.4	8.4	15.2	4.0	7.2	9.6	20.4	32.4
	Rank	0.8	55.2	69.6	85.6	95.6	5.6	91.2	95.2	98.8	99.6

Notes: [a]The equally weighted NASDAQ market is used in the estimation. [b]The parametric standardized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.

noted by Cowan (1992). If *a priori* information suggests that only one tail tests are of interest, the sign statistic based on Theil estimation may provide a powerful alternative.

Results for a rank test based on Theil estimation for the smaller NASDAQ portfolios are similar, but more pronounced, than the results presented in Table 3 for portfolios of 50 NASDAQ securities. Tables 4 and 5 show the rank statistic estimated under the Theil method exhibits more power than the OLS based rank statistic for both lower and upper tail tests with the differences being most evident at the 1% significance level. For example, Table 4 shows the rank statistic's ability to detect a one-half percent inducement in abnormal performance (at the 1% significance level) in portfolios of size 25 is more than doubled by Theil estimation versus OLS estimation. Table 5 shows the rank statistic's ability to detect a one-quarter percent inducement in abnormal performance (at the 1%

Table 5. A comparison of estimation methods for the market model of security returns in event studies. Numbers in the represent#the percentage of 250 random samples of 10 NASDAQ securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	0.25	0.5	1	1.5	0[c]	0.25	0.5	1	1.5
OLS	STD	1.6	4.4	5.2	16.0	34.4	5.2	10.4	17.2	38.4	63.2
	Sign	1.6	8.8	23.2	40.4	53.6	6.0	34.8	57.2	74.0	85.6
	Rank	1.2	5.6	15.2	36.4	59.6	5.2	37.2	54.0	76.8	89.2
Theil	STD	2.8	4.4	6.0	18.0	38.8	7.2	12.4	19.6	40.8	68.8
	Sign	1.2	63.2	68.0	78.8	86.4	4.4	92.0	94.0	96.4	98.0
	Rank	1.2	26.4	32.4	48.8	69.6	5.6	68.0	72.8	84.4	90.8
		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	−0.25	−0.5	−1	−1.5	0[c]	−0.25	−0.5	−1	−1.5
OLS	STD	2.0	2.8	4.4	15.6	34.8	7.6	10.4	16.8	38.0	65.6
	Sign	0.4	3.2	4.4	9.6	14.8	4.0	14.8	26.0	43.2	54.8
	Rank	0.4	5.6	14.0	32.8	53.2	5.6	32.4	48.8	73.6	86.8
Theil	STD	1.6	3.2	3.2	11.2	29.6	6.0	9.6	14.0	34.4	60.0
	Sign	0.4	1.2	1.6	2.8	4.0	2.4	4.0	5.6	10.0	14.0
	Rank	1.6	24.0	28.8	42.0	61.2	5.6	63.6	70.8	80.8	89.6

Notes: [a]The equally weighted NASDAQ market is used in the estimation. [b]The parametric standarized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.

significance level) in portfolios of size 10 is more than tripled by Theil estimation versus OLS estimation.

Consistent with previous research, Table 1 reported less departure from normality for returns from the NYSE/AMEX markets. The appendix provides tables containing results for the NYSE/AMEX markets for various portfolio sizes. Tables A-2 through A-4 show almost all test statistics appear to be well specified. Even the combination of Theil methodology and the standardized test statistic appears to be well specified in several cases. These results show that complete nonparametric approaches are well specified when the underlying return distribution dose not depart greatly from normality.

Similar to the results for NASDAQ, the results for NYSE/AMEX provided in the appendix show that the combination of the Theil methodology and a sign test statistic provide relatively low power in lower tail tests. The complete nonparametric combination of Theil estimation and a rank statistic provides no less than the same power as the rank test statistic based on OLS.

In summary, the advantages of using Theil's nonparametric technique in the estimation of the market model are greater for NASDAQ securities and small portfolios than for NYSE/AMEX securities and larger portfolios.

C. Power of test statistics with a variance increase

Variance increases which may occur with an event will alter the probability of a Type I error. The failure to consider a true variance increase associated with an event will lead researchers to overstate the true significance of findings. Following Brown and Warner (1985), we simulate a variance increase in our analysis by summing the abnormal returns from day 0 and day +5.

The effects of a variance increase are presented in Tables 6 for portfolios of 50 securities from the NASDAQ market.[17] Similar to with Campbell and Wasley (1993), the parametric standardized statistic is misspecified regardless of the market, estimation method, or sample size considered.[18] The OLS based sign statistic is generally well specified across both markets and methodologies for all sample sizes under conditions of variance increases. The sign statistic based on Theil estimation is misspecified in upper tail tests due to its positive bias before the variance increase and therefore performs poorly in lower tail tests. The rank statistic utilizing Theil's estimation exhibits greater (similar) power than its OLS counterpart in NASDAQ (NYSE) samples.[19]

Overall, the results discussed in parts B and C of this section show that Theil's nonparametric estimation offers potential improvements in the power to detect abnormal performance relative to the traditionally used OLS methodology. The benefits of Theil's nonparametric estimation are associated with the departures from normality evident in security return distributions. Nonparametric estimation produces improvements for detecting abnormal performance in the NASDAQ market which is characterized by a high degree of non-normality. Theil estimation offers comparable performance to OLS estimation for large NYSE samples, and small improvements for smaller NYSE portfolios. The introduction of an event induced variance increase does not diminish the performance of Theil estimation relative to OLS estimation. The combination of Theil's nonparametric

Table 6. A comparison of estimation methods for the market model of security returns in event studies when variance has been doubled. Numbers in the represent#the percentage of 250 random samples of 50 NASDAQ securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	0.25	0.5	1	1.5	0[c]	0.25	0.5	1	1.5
OLS	STD	11.2	18.0	30.0	72.4	90.4	17.2	36.4	56.0	86.4	97.6
	Sign	1.2	24.4	64.0	92.0	96.8	6.0	70.0	91.2	99.2	100.0
	Rank	1.2	22.4	50.4	89.2	98.4	7.6	66.8	91.2	100.0	100.0
Theil	STD	12.4	21.2	37.2	76.8	93.6	22.4	43.2	59.2	94.4	98.0
	Sign	6.8	98.8	99.6	100.0	100.0	24.0	100.0	100.0	100.0	100.0
	Rank	2.4	61.2	75.2	94	98.8	8.8	94.8	98.0	100.0	100.0
		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	−0.25	−0.5	−1	−1.5	0[c]	−0.25	−0.5	−1	−1.5
OLS	STD	4.4	11.2	22.0	61.2	86.4	11.2	24.0	41.6	78.0	94.4
	Sign	0.0	2.0	11.6	42.4	68.4	0.4	29.2	56.8	81.6	92.8
	Rank	0.8	22.8	52.0	86.4	95.6	4.4	69.2	89.2	99.2	100.0
Theil	STD	3.6	6.8	17.6	51.6	81.2	8.4	17.2	35.6	71.2	94.0
	Sign	0.0	0.0	0.0	1.6	6.8	0.4	0.8	0.8	5.6	15.6
	Rank	0.8	61.6	74.4	89.2	96.4	5.2	95.2	95.2	99.6	100.0

Notes: [a]The equally weighted NASDAQ market is used in the estimation. [b]The parametric standardized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.

estimation procedure and the rank statistic provides similar (or greater) power in the symmetrical detection of abnormal performance under a variety of different scenarios.

6. *Summary and potential applications*

A. *Summary*

The lack of normality in security returns prompted the introduction of nonparametric test statistics in event studies. The parametric estimation of the model itself, however, has been overlooked in the literature. This study incorporates Theil's nonparametric regression technique as an alternative means for estimating abnormal security returns for the frequently used market model. Simulations using NASDAQ and NYSE/AMEX securities are conducted to compare Theil's performance with that of the traditionally employed OLS estimation.

Theil's nonparametric estimation is found to offer potential improvements in power to detect abnormal performance over the traditional OLS estimation technique. The benefits of nonparametric estimation are associated with the degree of non-normality present in security returns. Theil's nonparametric estimation procedure offers comparable performance to OLS for the NYSE/AMEX samples which exhibit only slight departures from normality. The complete nonparametric combination of Theil estimation along with a rank test statistic provides relatively greater power in detecting abnormal performance when examining smaller NYSE portfolios or the NASDAQ market which is characterized by a higher degree of non-normality. The relative benefits of nonparametric estimation of the market model are not diminished under the condition of an event induced variance increase.

Overall, the combination of Theil's nonparametric estimation procedure and the rank statistic is recommended due to its comparable specification with other methods and less restrictive assumptions.

B. Potential applications and future research

The results discussed above indicate that Theil's nonparametric estimation technique should be employed when using the market model in event studies and the underlying stock returns might not come from a normal distribution. Non-normality may be a major concern in many cases beyond the examination of individual stocks, small samples, and NASDAQ samples. For example, monthly stock returns from emerging markets exhibit high levels of non-normality. Non-normal returns are also commonplace for real estate and other frequently analyzed return series.

Similar to Corrado (1989), this study focuses on a one day event window. Kothari and Warner (1997) report parametric test statistics for long-horizon abnormal returns around firm specific events are severely misspecified. These authors recommend nonparametric procedures such as bootstrap. Barber and Lyon (1997) report that misspecification of parametric statistics in long-horizon event studies may be overcome by matching sample firms to control firms of similar size and book to market ratios. Future research should examine the ability of Theil methodology as well as other techniques (or combinations thereof) to overcome misspecification problems under a variety of conditions.

Appendix

Tables A-1 through A-5 provide results for portfolios of various sizes made up of NYSE/AMEX securities.

Table A-1. Summary statistics for the empirical distribution of test statistics for NYSE/AMEX portfolio sizes of 10, 25, and 50 securities. The empirical distributions are based on 250 values of the test statistics for each portfolio size. Securities and event dates are randomly selected with replacement

NYSE/AMEX

Portfolio Size	Estimation Method	Test Statistic	Mean[a]	Standard Deviation	t-Statistic	Skewness	Excess Kurtosis	Test for Normality
50	OLS	STD	0.030	1.001	0.477	−0.144	−0.098	0.6995
		Sign	−0.024	0.997	−0.379	−0.169	0.655	0.9160
		Rank	−0.020	0.965	−0.321	−0.283	0.491	0.4875
	THEIL	STD	0.319	1.008	5.005	−0.168	−0.203	0.3864
		Sign	0.004	0.964	0.072	−0.333	1.217	0.2737
		Rank	−0.030	0.981	−0.480	−0.256	0.257	0.3257
25	OLS	STD	0.028	1.014	0.441	0.247	−0.165	0.2957
		Sign	−0.020	1.046	−0.309	−0.407	−0.271	0.4053
		Rank	0.005	1.000	0.078	0.110	−0.378	0.2340
	THEIL	STD	0.221	1.027	3.399	0.253	−0.152	0.2058
		Sign	0.008	1.013	0.128	−0.033	0.039	0.3917
		Rank	−0.014	1.017	−0.213	0.047	−0.360	0.1928
10	OLS	STD	−0.029	1.034	−0.449	0.125	2.226	0.9908
		Sign	−0.028	1.036	−0.428	−0.039	−0.082	0.1545
		Rank	−0.031	1.021	−0.478	−0.239	0.280	0.7727
	THEIL	STD	0.098	1.041	1.493	0.132	2.379	0.9678
		Sign	−0.007	0.985	−0.111	−0.154	−0.391	0.0442
		Rank	−0.041	1.030	−0.627	−0.278	0.287	0.7448

Notes: [a]No abnormal performance has been artificially introduced.

Table A-2. A comparison of estimation methods for the market model of security returns in event studies. Numbers in the represent the percentage of 250 random samples of 50 NYSE/AMEX securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	0.25	0.5	1	1.5	0[c]	0.25	0.5	1	1.5
OLS	STD	0.4	8	32	87.2	99.6	4.4	24.8	56	96.8	100
	Sign	1.2	10.8	41.2	90.8	100	3.2	31.6	70	99.6	100
	Rank	2	10.8	39.6	95.2	100	4.4	27.2	70.8	99.2	100
Theil	STD	0.8	14.4	41.6	92.8	100	11.2	34	67.2	98	100
	Sign	0.4	27.6	64.4	94.8	100	5.2	58.8	81.6	100	100
	Rank	0	14	46.4	96.4	100	5.6	35.2	72.4	99.2	100

		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic	0[c]	−0.25	−0.5	−1	−1.5	0[c]	−0.25	−0.5	−1	−1.5
OLS	STD	2	6.4	29.2	86.4	100	4.4	21.6	55.6	98	100
	Sign	1.6	8	28.4	80.4	98.8	5.2	27.6	56.8	95.2	100
	Rank	1.2	9.6	39.2	96	100	4.8	30	67.6	98.8	100
Theil	STD	0.4	4.4	20	81.2	99.6	2.8	14.4	40.8	93.6	100
	Sign	1.2	6.8	22	76.8	95.6	4.4	22.8	52.4	91.6	99.6
	Rank	0	13.6	47.2	95.6	100	4.8	39.2	73.2	100	100

Notes: [a]The equally weighted NYSE/AMEX market is used in the estimation. [b]The parametric standardized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.

Table A-3. A comparison of estimation methods for the market model of security returns in event studies. Numbers in the represent#the percentage of 250 random samples of 25 NYSE/AMEX securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	0.25	0.5	1	1.5	0[c]	0.25	0.5	1	1.5
OLS	STD	1.2	5.6	16.8	57.6	92.8	6.0	16.8	35.6	80.0	98.8
	Sign	0.4	6.0	17.6	59.6	86.8	6.0	21.2	45.6	81.6	96.4
	Rank	0.8	6.8	22.0	65.2	95.2	5.2	23.2	42.8	88.4	99.2
Theil	STD	2.8	8.0	20.0	60.8	94.0	8.4	20.8	40.0	86.8	98.8
	Sign	0.4	12.8	31.6	67.2	90.8	6.0	36.8	53.2	85.6	98.0
	Rank	0.8	10.0	22.4	65.2	95.6	6.0	24.4	44.4	88.0	99.2

		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic	0[a]	−0.25	−0.5	−1	−1.5	0[c]	−0.25	−0.5	−1	−1.5
OLS	STD	0.8	3.2	13.2	59.2	89.6	3.6	13.6	36.4	79.6	96.0
	Sign	1.6	6.8	14.4	40.8	66.0	5.6	17.6	35.2	69.6	92.4
	Rank	0.8	6.0	21.6	63.6	92.8	3.6	21.6	45.6	87.2	99.2
Theil	STD	0.8	2.0	9.2	52.4	84.8	2.4	10.0	30.8	73.6	94.0
	Sign	1.6	3.6	12.0	37.2	63.2	4.8	17.6	29.2	65.2	89.2
	Rank	1.6	7.2	25.6	65.2	93.2	5.2	28.4	47.6	86.0	99.2

Notes: [a]The equally weighted NYSE/AMEX market is used in the estimation. [b]The parametric standardized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.

Table A-4. A comparison of estimation methods for the market model of security returns in event studies. Numbers in the represent#the percentage of 250 random samples of 10 NYSE/AMEX securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	0.25	0.5	1	1.5	0[c]	0.25	0.5	1	1.5
OLS	STD	2.0	2.0	6.0	21.6	52.0	4.8	6.8	17.6	47.6	76.4
	Sign	0.8	2.0	3.6	15.6	35.2	2.4	8.0	18.4	45:6	70.8
	Rank	0.8	2.8	5.6	22.8	59.2	2.8	10.4	21.6	56.8	83.6
Theil	STD	2.0	3.2	6.8	26.4	54.8	6.8	8.4	22.4	51.6	80.4
	Sign	0.4	4.8	8.0	21.6	45.6	6.8	13.6	26.4	56.8	77.2
	Rank	0.8	2.8	5.2	26.0	60.4	8.4	12.8	24.4	58.8	84.0

		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic	0[c]	−0.25	−0.5	−1	−1.5	0[c]	−0.25	−0.5	−1	−1.5
OLS	STD	1.2	3.6	6.4	24.0	54.8	4.8	10.4	20.4	50.8	78.0
	Sign	1.2	3.6	8.0	19.2	31.6	8.0	14.0	26.0	43.6	59.2
	Rank	1.2	4.4	10.8	28.4	51.6	6.8	15.6	24.4	52.8	78.4
Theil	STD	1.2	2.0	6.0	20.8	48.0	4.8	8.8	16.0	45.6	71.6
	Sign	0.8	1.2	4.4	18.4	29.6	2.8	14.0	21.2	38.0	53.2
	Rank	1.6	6.0	11.2	30.8	50.8	3.2	17.6	26.8	53.6	79.6

[a]The equally weighted NYSE/AMEX market is used in the estimation. [b]The parametric standardized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.

Table A-5. A comparison of estimation methods for the market model of security returns in event studies when variance has been doubled. Numbers in the represent#the percentage of 250 random samples of 50 NYSE/AMEX securities which reject the null hypothesis of no abnormal performance. Significance tests are considered well specified under the null hypothesis at the 5% (1%) level if the percent of rejection falls between 2% and 8% (0% and 2.2%)

		Upper tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	0.25	0.5	1	1.5	0[c]	0.25	0.5	1	1.5
OLS	STD	10.4	21.6	39.6	81.2	97.6	19.2	34.8	58.4	90.0	98.8
	Sign	2.0	8.4	21.6	62.4	91.2	6.8	24.4	44.8	85.2	97.6
	Rank	1.6	12.4	28.0	74.4	96.8	10.8	26.8	47.6	89.6	98.8
Theil	STD	14.0	26.0	46.4	85.2	98.4	22.4	40.4	66.8	93.2	99.6
	Sign	1.2	16.4	27.2	67.2	92.0	7.2	35.2	58.0	90.0	98.4
	Rank	1.2	14.4	29.2	74.8	96.4	10.0	28.8	47.6	90.0	98.8

		Lower tail test									
		1% Significance Level					5% Significance Level				
		Abnormal Performance Induced					Abnormal Performance Induced				
Estimation of Market Model[a]	Test Statistic[b]	0[c]	−0.25	−0.5	−1	−1.5	0[c]	−0.25	−0.5	−1	−1.5
OLS	STD	6.0	15.2	29.6	76.4	96.4	11.6	26.8	51.2	85.6	98.8
	Sign	0.4	1.6	7.6	34.0	69.6	3.2	10.8	20.4	62.4	88.4
	Rank	2.4	10.0	26.8	72.4	95.6	6.8	23.2	49.2	86.8	99.6
Theil	STD	4.0	10.0	23.6	70.0	94.0	8.4	20.0	38.4	81.2	98.4
	Sign	0.4	1.2	4.8	31.6	60.4	2.0	8.8	21.2	58.0	83.6
	Rank	2.8	11.2	28.8	72.4	96.0	7.2	29.6	51.2	87.2	99.6

Notes: [a]The equally weighted NYSE/AMEX market is used in the estimation. [b]The parametric standardized statistic is denoted as STD, the nonparametric statistics are sign and rank. [c]Abnormal performance is artificially introduced by adding the indicated percent (0 to ± 1.5%) to the event day of each security.\

Notes

1. Two other commonly employed models are the mean adjusted model and the market adjusted model. The average security return during an estimation period provides the expectation for returns in the mean adjusted model where as the return for the overall market is the expectation for the market adjusted model. Patell (1976), Brown and Warner (1980), Peterson (1989), and MacKinlay (1997) review standard event study methodologies.
2. The common denominator, $\sum_{i<j}(RM_i - RM_j)^2$, has been omitted for clarity.
3. Errors in the estimation of Beta will be transferred to the measurement of abnormal returns, their relative ranks and subsequent analysis.
4. Dielman and Pfaffenberger (1982) suggest a high interest in robust procedures for regression models is due to OLS sensitivity to outliers and that often data do not conform to the normality assumption required for inference from OLS estimates.
5. Robust estimators of location fall into three main categories: maximum likelihood approaches, linear combinations of order statistics, and ranking approaches. There exists a wide variety of alternatives to choose between under these categories as well as numerous possible adaptive approaches.
6. Other alternatives exist. For example, the least absolute value (LAV) regression method may perform in a similar manner.
7. Talwar (1993) examines a t-distribution with 4 degrees of freedom, a symmetric stable, a chi-square with 4 degrees of freedom, and autoregressive conditional heteroscedasticity.
8. Theil's original model calculates the full set of slopes: N(N-1)/2 calculations. The incomplete method, in contrast, requires only N/2 calculations and was found to be almost as efficient by Hussain and Sprent (1983).
9. To facilitate comparisons, we follow the experimental design as described in previous research (Campbell and Wasley, 1993; Brown and Warner, 1980, 1985). Sampling with replacement leads to firms with longer time series having a higher probability of being selected. Each time a security is selected, an event date (day 0) is randomly assigned for that security. Market return data is then taken from the CRSP files to correspond to each securities estimation and event windows.
10. CRSP identifies returns as missing when there is not enough information to compute a stock return. Similar to previous research, we require that firms have enough returns in the estimation window to carry out the estimation of expected returns with some confidence. The requirement that there be no missing returns in the event window is also customary to avoid the problem of not being able to compute required test statistics on the randomly assigned event dates. In forming the portfolios of various sizes, if a security does not meet the cited criteria, we randomly select another security until we reach the desired portfolio size.
11. Parametric statistics based on cross-sectional procedures are not reported due to their inefficiency vis-à-vis the standardized test statistic.
12. The nonparametric statistics do not rely upon a normality assumption. However, nonparametric statistics do make use of abnormal returns determined by the estimated parameters for the market model. The magnitude of abnormal returns (and hence their sign and rank) depend on the employed estimation procedure.
13. This is consistent with Cowan (1992) that reports a higher standard deviation of individual stocks abnormal returns from NASDAQ (3.4%) than from the NYSE (2.6%).
14. Tables presenting results for NYSE/AMEX portfolios are in the appendix.
15. Test statistics for a given value of alpha level may be calculated as follows: $Z = (p - \alpha)/(\alpha(1-\alpha)/250)^{\wedge(1/2)}$ where p = observed rejection rate.
16. Differences in the performance of estimation procedures were generally less pronounced for the NYSE/AMEX portfolios of 50 securities (see Table A-2). However, smaller NYSE/AMEX portfolios produced differences in performance similar to those discussed here.
17. Tables presenting results for smaller NASDAQ or NYSE/AMEX portfolios are in a appendix available from the authors upon request.
18. Other techniques have been suggested to overcome the problems associated with event-induced variance increases. For example see Boemer, Musumeci, and Poulsen (1991).
19. For smaller portfolios, the rank statistics estimated under either method are comparable in terms of specification and both have a tendency to be slightly misspecified in upper tail tests.

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