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Event-Study Methodology: Correction for Cross-Sectional Correlation in Standardized Abnormal Return Tests*

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Abstract

Standardized methods by Patell (1976) and Boehmer, Musumeci, and Poulsen (1991) have been shown to outperform traditional, non-standardized tests in event studies. However, standardized tests are valid only if there are no cross-sectional correlations between the observations' returns. In this paper we propose simple corrections to these test statistics to account for such correlation. To demonstrate the usefulness of correcting for cross-sectional correlations in standardized abnormal return tests, we conduct simulation analyses of abnormal stock return performance using daily returns. The simulation results show that even moderate cross-sectional correlation in the residual returns causes substantial over-rejection of the null hypothesis by the original statistics. Results for the corrected statistics reject the null hypothesis on average at around the nominal rate.

Key Words: Event studies; Cross-sectional correlation; Statistical simulation

JEL Classification: G14; C10; C15

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I. Introduction

A basic assumption in traditional event study methodology is that the abnormal returns are cross-sectionally uncorrelated. This assumption is valid when the event day is not common to the firms. Even in the case when the event day is common, if the firms are not from the same industry, Brown and Warner (1982, 1985) show that use of the market model to derive the abnormal return reduces the inter-correlations virtually to zero and, hence, can be ignored in the analysis. Nevertheless, it is well known that, if the firms are from the same industry or have some other commonalities, extraction of the market factor may not reduce the cross-sectional residual correlation. Consequently, use of test statistics relying on independence understate the standard errors and lead to severe over-rejection of the null hypothesis of no event effect when it is true.

The traditional approach to account for correlation between returns is the so-called portfolio method suggested by Jaffe (1974), in which the firm returns are aggregated in an equally-weighted portfolio and the abnormal returns of the portfolio are investigated. While this captures the contemporaneous dependency between the returns, it is generally sub-optimal.
In this regard, there have been several other attempts in the literature to solve the contemporaneous correlation problem [See Khotari and Warner (2005) for a review]. The Generalized Least Squares (GLS) is known to be optimal under certain assumptions, but it requires accurate estimation of the covariance matrix of the returns, which is not always possible, particularly if the number of firms is larger than the number of time points in the estimation period. However, as noted above, ignoring the contemporaneous correlations may introduce

extensive downward bias into the standard deviation and thereby overstate the *t*-statistic, which leads to over-rejection of the null hypothesis. Also, the cost of estimating the large number of covariance parameters needed in GLS has been found to introduce even more inaccuracy into the standard errors than it eliminates, thereby making the test results even worse [See, for example, Malatesta (1986)]. Futhermore, Chandra and Balachandran (1990) argue that GLS is highly sensitive to model mis-specification, which may lead to inefficient test results even if the covariance matrix is known. They conclude that GLS should be avoided in event studies because the correct model specification is rarely known for certain. Consequently, Chandra and Balachandran (1990) recommend the use of nongeneralized least squares, which essentially reduces to the portfolio tests cited above.

Particularly relevant to the present study, methods based on standardized abnormal returns have been found to outperform those based on non-standardized returns. The most widely used standardized methods are the Patell (1976) *t*-statistic and the Boehmer, Musumeci, and Poulsen (hereafter BMP) (1991) *t*-statistic. However, both of these standardized tests rely on the assumption that the abnormal returns are contemporaneously uncorrelated. At least in the case of the Patell (1976) approach, one method of resolving the contemporaneous correlation problem (as suggested above) is to aggregate the standardized abnormal returns using an equally-weighted portfolio and compute the *t*-statistic from the portfolio returns. Unfortunately, the portfolio method does not work in the popular BMP (1991) approach. In an attempt to resolve potential bias in test statistics arising from cross-sectional correlations, the present paper contributes to the event study methodology literature by deriving simple formulas that correct the original Patell *t*-statistic and the original BMP *t*-statistic for cross-sectional correlations.

The remainder of this paper is organized as follows. Section II provides corrected test statistics for abnormal returns in event studies with cross-sectional correlation between observations. Section III discusses the simulation design. Section IV presents the empirical results. Section V concludes.

II. Correlation Corrected Test Statistics for Standardized Abnormal Returns

Patell's (1976) statistic is of the form

(1) $$t_P = \frac{\bar{A}\sqrt{n}}{\sqrt{(m-2)/(m-4)}} = \bar{A}\sqrt{\frac{n \times (m-4)}{m-2}} ,$$

where $\bar{A}$ is the average of standardized abnormal returns over the sample of n firms on the event day, and m is the number of observations (i.e., days, months, etc.) in the estimation period. The standardized abnormal returns are calculated by dividing the event period residual by the standard deviation of the estimation period residual, corrected by the prediction error [See, for example, Campbell, Lo, and MacKinlay (1997, p. 160)]. Boehmer et al. (1991) estimate the cross-sectional variance of the standardized abnormal returns and define a *t*-statistic (BMP *t*-statistic) as

(2) $$t_B = \frac{\bar{A}\sqrt{n}}{s} ,$$

where s is the (cross-sectional) standard deviation of the standardized abnormal returns.
If the event day is the same for the firms, the Patell and BMP *t*-statistics do not account for contemporaneous return correlations. In the literature various methods have been suggested to deal with this problem. Generalized least squares (GLS) is the optimal solution if the return covariance matrix can be estimated accurately and the abnormal return generating model is known [See, for example, Chandra and Balachandran (1990)]. However, these requirements are

rarely met. Probably the most common way to circumvent this problem is the so-called *portfolio method*, where firm returns are aggregated in an equally-weighted portfolio. This method implicitly accounts for the contemporaneous correlations. Nevertheless, in comparison to the GLS, it does not lead to optimal estimation of the event effect. The advantage of the Patel (1976) method as well as the BMP (1991) method is that they weight individual observations by the inverse of the standard deviation, which implies that more volatile (i.e., more noisy) observations get less weight in the averaging than the less volatile and hence more reliable observations. This is roughly the idea in the GLS, where the observations are weighted by the elements of the inverse of (residual) return covariance matrix. The BMP statistic has gained popularity over the Patell (1976) statistic because it has been found to be more robust with respect to possible volatility changes associated with the event. Neither of these methods, however, accounts for the possible cross-sectional correlations that can exist when the event day is the same for the firms. Because stock returns are typically positively correlated, ignoring such correlations leads to underestimation of the abnormal return variance and, in turn, over-rejection of the null hypothesis of no event effect when it is true. Consequently, we propose below simple corrections to these statistics to account for the cross-correlations.

Implicitly, the Patell (1976) and BMP (1991) tests assume that the standardized abnormal returns are homoscedastic and therefore have the same variance. Indeed, if there is no volatility effect due to the event, all standardized abnormal returns would have roughly a unit variance and lead to the Patell (1976) t-statistic. The BMP approach relaxes the no-volatility-impact, and estimates the (common) event-day-volatility cross-sectionally with the usual sample standard deviation. However, when the event day is the same for all firms, the standardized abnormal returns are potentially correlated, which can bias the volatility estimates in both cases.

A. Single Common Event Day

Let σ_A^2 be the common population variance of the standardized abnormal returns (which equals (m-2)/(m-4) if there is no event induced variance), and let σ_{ij} denote the population covariance of standardized abnormal returns for securities i and j. Using simple algebra, the variance of the mean of the standardized abnormal returns over n firms is

(3) $$\sigma_{\bar{A}}^2 = \frac{1}{n}\sigma_A^2 + \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j\neq i}\sigma_{ij} .$$

Because the variances are the same for all standardized abnormal returns, i.e., $\sigma_i^2 = \sigma_j^2 = \sigma_A^2$, the covariances can be written as

(4) $$\sigma_{ij} = \sigma_i \sigma_j \rho_{ij} = \sigma_A^2 \rho_{ij} ,$$

where ρ_{ij} is the correlation of the abnormal returns of stocks i and j. As such, we can write equation (3) as

(5) $$\sigma_{\bar{A}}^2 = \sigma_A^2\left(\frac{1}{n} + \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j\neq i}\rho_{ij}\right) = \frac{\sigma_A^2}{n}\left(1 + (n-1)\bar{\rho}\right),$$

where $\bar{\rho}$ is the average correlation of the abnormal returns. Note that, in order to keep the correlation matrix positive definite, equation (5) implies that the return correlations cannot be highly negative on average. Assuming that the event does not change the residual correlation, the average correlation of the abnormal returns can be estimated by averaging the sample correlations of the estimation period residuals. In the Patell (1976) statistic $\sigma_A^2 = (m-2)/(m-4)$, where m is the number of observations.[1] Accordingly, using equation (5), a correlation-adjusted Patell t-test, t_{AP}, becomes

(6) $$t_{AP} = \frac{\bar{A}\sqrt{n}}{\sqrt{(m-2)/(m-4)}\sqrt{1+(n-1)\bar{r}}} = \frac{t_P}{\sqrt{1+(n-1)\bar{r}}},$$

where $\bar{r}$ is the average of the sample correlations of estimation period residuals, and t_P is the Patell (1976) *t*-statistic defined in equation (1).

In the BMP *t*-statistic the standard deviation is estimated cross-sectionally as the square root of the sample variance

(7) $$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(A_i - \bar{A})^2 .$$

Following Sefcik and Thompson (1986, p. 327), given the assumption that $E[A_i] = \mu_A$ (See Appendix A for details), it can be easily shown that

(8) $$E[s^2] = (1-\bar{\rho})\sigma_A^2 .$$

Thus, equation (7) is a biased estimator of the variance σ_A^2. Normally, because $\bar{\rho}$ is positive, s^2 understates the true cross-sectional variance. Because $E[s^2/(1-\bar{\rho})] = \sigma_A^2$, a feasible estimator of the variance σ_A^2 is

(9) $$s_A^2 = \frac{s^2}{1-\bar{r}},$$

where $\bar{r}$ is the average of the sample cross-correlations of the estimation period residuals. Therefore, an estimator of the variance of the mean abnormal return $\bar{A}$ is obtained by replacing the parameters in equation (5) by the estimators so that

(10) $$s_{\bar{A}}^2 = \frac{s_A^2}{n}(1+(n-1)\bar{r}) .$$

Using these results in the original BMP *t*-statistic given by equation (2), the correlation-adjusted *t*-statistic, t_{AB}, becomes

(11) $$t_{AB} = \frac{\bar{A}}{s_{\bar{A}}} = \frac{\bar{A}\sqrt{n}}{s_A\sqrt{1+(n-1)\bar{r}}} = t_B\sqrt{\frac{1-\bar{r}}{1+(n-1)\bar{r}}}\ ,$$

where t_B is the BMP *t*-statistic given in equation (2). From equation (11) it is immediately obvious that, if the return correlations are zero, the modified statistic reduces to the original *t*-statistic.

As seen from equations (6) and (11), the severity of cross-sectional correlation in the *t*-statistics is both a function of the average correlation and number of firms. It is important to note that underestimation of the variance due to the correlation causes a more pronounced over-rejection of the true null-hypothesis in the two-sided test than in the one-sided test. This is obvious from Table 1, where the size problems of the unadjusted test statistics are numerically demonstrated for one-sided and two-sided tests at the nominal 5 percent level for different sample sizes and degrees of cross-sectional correlation.

Typically, market model residual cross-sectional correlations in intra-industry returns are fairly low. For example, using U.S. data, Bernard (1987) finds an average correlation of 0.04 for daily observations. However, as shown in Table 1, we find that, even with low average correlation, problems emerge (especially in the two-sided test) at a sample size of about 10 firms in the event study. Based on an average correlation of only 0.05, the true rejection probabilities at the nominal 5 percent level in a sample of 10 firms for the two-sided tests are 0.10 for the Patell test and 0.11 for the BMP test. In a larger sample of 100 firms, the true rejection probabilities with average correlation of 0.05 are already over 0.40 in the two-sided test and about 0.25 in the one-sided test. That is, instead of a 5 percent rejection rate, the true null hypothesis would be rejected with more than a 40 percent (25 percent) probability in the two-sided (one-sided) test. Thus, although the market model obviously captures a large share of the return contemporaneous correlation, the remaining relatively small correlation still materially biases the significance levels with even moderate sample sizes.

B. Clustered Common Event Days

Suppose next that we have q clusterings or groupings of the event days, where in each group the event day is the same for the corresponding firms. Then the correlations of the non-overlapping event-day-groups are zero and the covariance matrix of the standardized abnormal returns is block-diagonal. Equivalently, we can think of having q industries, where all have the same event day but the between-industry correlations are zero. In both cases the kth block corresponds to the covariance matrix of the firms belonging to the kth group with covariance matrix Σ_k, $k = 1,\ldots,q$. The average standardized abnormal return is $\overline{A} = \frac{1}{n}\sum_{k=1}^{q} n_k \overline{A}_k$, where $\overline{A}_k$ is the average standardized abnormal return in subgroup k, and n_k is the number of firms in subgroup k. Again assuming that within each sub-group the variances of the standardized returns are the same, the variance of $\overline{A}_k$ is of the form shown in equation (3). Consequently, the variance of the average abnormal return over all firms becomes

$$\sigma_{\overline{A}}^2 = \frac{1}{n^2}\sum_{k=1}^{q} n_k^2 \sigma_{\overline{A}_k}^2 = \frac{1}{n^2}\sum_{k=1}^{q} n_k \sigma_k^2 (1 + (n_k - 1)\overline{\rho}_k), \tag{12}$$

where $\sigma_{\overline{A}_k}^2$ is the variance of the average abnormal returns in group k, σ_k^2 is the variance of the standardized abnormal return in group k, and $\overline{\rho}_k$ is the average abnormal return correlation in group k.[2]

For the sake of simplicity, assume that the estimation periods for all firms are the same. Then in the Patell (1976) statistic $\sigma_k^2 = (m-2)/(m-4)$ for all $k = 1,\ldots,q$. The average of the cross-sectional sample correlations of the residuals, $\overline{r}_k$, for group k are defined as

(13) $$\bar{r}_k = \frac{1}{n_k(n_k-1)} \sum_{i=1}^{n_k} \sum_{\substack{j=1 \\ j \neq i}}^{n_k} r_{ij,k} ,$$

where $r_{ij,k}$ is the sample correlation of the market model residuals of returns *i* and *j* in group *k* calculated over the sample period. Replacing $\bar{\rho}_k$ in equation (12) by the estimator (13) gives the correlation adjusted Patell *t*-statistic

(14) $$t_{AP} = \frac{\bar{A} \times n\sqrt{(m-4)/(m-2)}}{\sqrt{\sum_{k=1}^{q} n_k \left(1 + (n_k - 1)\bar{r}_k\right)}} = t_P \sqrt{\frac{n}{\sum_{k=1}^{q} n_k \left(1 + (n_k - 1)\bar{r}_k\right)}} ,$$

where t_P is the Patell (1976) *t*-statistic. We can write further

(15) $$\begin{aligned} \sum_{k=1}^{q} n_k \left(1 + (n_k - 1)\bar{r}_k\right) &= n + \sum_{k=1}^{q} n_k (n_k - 1)\bar{r}_k \\ &= n\left(1 + (n-1)\tilde{\bar{r}}\right), \end{aligned}$$

where

(16) $$\tilde{\bar{r}} = \frac{1}{n(n-1)} \sum_{k=1}^{q} n_k (n_k - 1)\bar{r}_k ,$$

such that $\tilde{\bar{r}}$ is the average sample correlations over the whole (block) correlation matrix with between-block sample correlations set to zero (i.e., a restricted average correlation estimator). Using these notations, we can write equation (14) in the same form as equation (6), such that

(17) $$t_{AP} = \frac{\bar{A}\sqrt{n}}{\sqrt{(m-2)/(m-4)}\sqrt{1 + (n-1)\tilde{\bar{r}}}} = \frac{t_P}{\sqrt{1 + (n-1)\tilde{\bar{r}}}} ,$$

where the only difference is that the unrestricted average correlation estimator, $\bar{r}$, is replaced by the restricted average correlation estimator, $\tilde{\bar{r}}$, defined in equation (16).

Estimating the abnormal return variance with cross-sectional estimator (7) as in the BMP t-statistic, and using similar methods provided in Appendix A, the expected value of the estimator in the grouped data can be straightforwardly shown to be

$$E\left[s^2\right] = \sigma_A^2 \frac{1}{n-1}\sum_{k=1}^{q} n_k\left(1-\frac{1}{n}\left(1+(n_k-1)\bar{\rho}_k\right)\right) \qquad (18)$$
$$= \sigma_A^2\left(1-\tilde{\bar{\rho}}\right),$$

where $\tilde{\bar{\rho}} = \frac{1}{n(n-1)}\sum_{q=1}^{q} n_k(n_k-1)\bar{\rho}_k$ is the average correlation over the whole correlation matrix including the zero correlations. Consequently, as in formula (9), a feasible estimator of σ_A^2 is

$$s_A^2 = \frac{s^2}{1-\tilde{\bar{r}}} \qquad (19)$$

where $\tilde{\bar{r}}$ is the restricted average sample correlation defined in equation (16). The corresponding correlation adjusted t-statistic for the grouped data is of the form (11) with $\bar{r}$ replaced again by the restricted average correlation estimator $\tilde{\bar{r}}$. That is, we have

$$t_{AB} = t_B\sqrt{\frac{1-\tilde{\bar{r}}}{1+(n-1)\tilde{\bar{r}}}}\,. \qquad (20)$$

III. Simulation design

A. Samples

We follow the design setup by Brown and Warner (1985) by constructing 250 independently drawn portfolios of sizes n = 50, 30, or 10 securities each. Because we are interested in the effect of cross-sectional correlation on the test statistic, we restrict the analyses to one industry. We selected the two-digit SIC industry code 36, which is one of the largest in terms of the number of firms with 1058 securities available on CRSP. According to the U.S. Department of Labor (www.osha.gov), this industry consists of firms in “Electronic and Other Electrical Equipment and Components, except Computer Equipment.” The total sample period covers CRSP daily returns from January 3, 1990 to December 31, 2004. In each round of simulation, initially a common randomly drawn event day is selected, which is set as date “0,” and then a sample of n securities are selected *without* replacement. In order for a security to be included in the sample, it must have at least 50 returns in the common estimation period (-249 through -11) and no missing returns in the 30 days surrounding the event date (-19 to +10).

B. Abnormal Returns

First, we generate fixed abnormal returns on day 0 by adding to the day 0 residual return an abnormal return of 0%, 0.5%, 1%, 2%, and 3%. Second, we allow for variance changes by adding to the day 0 residual return abnormal returns generated from the multivariate normal distribution with constant mean vectors of 0%, 0.5%, 1%, 2%, and 3% and a 50×50 covariance matrix Σ equal to the estimation period cross-sectional covariance matrix of the market model residuals. We increase the variance (covariances) by factor *c* in the manner described in Boehmer et al. (1991), such that the event induces additional variance-covariance is $c\Sigma$, where *c* is a constant equal to 0, 0.5, 1, or 2. Thus, the total covariance matrix in the event day 0 is $\Sigma_c = (1+c)\Sigma$, which implies that $c = 0$ corresponds to a no event-induced variance and $c = 2$ a variance of 3 times the non-event variance, or $\sqrt{3} \approx 1.73$ times the non-event standard deviation. It is notable that the correlations of the residual returns do not change with these variance-covariance increments. In the estimation of the market model, we use the equally-weighted version of the SP500 index as the market portfolio.

C. Test Statistics

In addition to the unadjusted Patell (1976) and BMP (1991) statistics given in equations (1) and (2), respectively, and their adjusted extensions given in equations (6) and (11), respectively, we report results for the traditional cross-sectional *t*-statistic

(21)
$$t_{cs} = \frac{\bar{A}\sqrt{n}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} s_i^2}},$$

where s_i^2 is the market model residual variance of security *i*. Additionally, we report the results for the standard portfolio method *t*-statistic

(22)
$$t_{pf} = \frac{\bar{A}}{s},$$

where

(23)
$$s = \sqrt{\frac{1}{237}\sum_{t=-249}^{-11}(R_t - \hat{\alpha} - \hat{\beta}R_{m,t})^2},$$

with $R_t = \frac{1}{n_t}\sum_{i=1}^{n_t} R_{i,t}$ corresponding to the equally-weighted portfolio return of n_t securities, $R_{m,t}$ is the equally-weighted SP500 return, and $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates of the market model parameters. Recall that this portfolio approach implicitly accounts for the cross-sectional correlations.

IV. Results

The simulation results are reported in Tables 2 through 6. Table 2 reports sample statistics under the null hypothesis of no event effect. The overall average of the return cross-correlations in the simulations is 0.077 for the samples of 50 securities and 0.078 for the samples of 30 and 10 securities. The average residual cross-correlation after extracting the market factor is 0.033 for the 50 securities samples and 0.036 for the 30 and 10 securities samples. All the average *t*-statistics are close to zero as expected due to no event effect being imposed. Although the average residual correlation is fairly low, its effect is quite dramatic with respect to the distributional properties of the unadjusted *t*-statistics. The third column shows that for all sample sizes (50, 30, or 10) the standard deviations of the traditional, Patell, and BMP statistics are typically more than 1.5 times the theoretical value of one under the null hypothesis. On the other hand, for the portfolio, adjusted Patell, and adjusted BMP methods the average standard deviations are close to the theoretical value of one, except for the adjusted BMP method in the case of $n = 10$ (small sample size) security portfolios. Thus, these preliminary results clearly demonstrate the fact that ignoring even small (average) correlation may substantially bias the distributional properties of the test statistics via underestimation of the true (residual) return variability.

Table 3 reports rejection rates using samples of 50, 30, and 10 securities at the 5 percent level for one- and two-tailed tests for the test statistics when the event has no mean effect but may increase variability. The second and third columns report results where there is neither a mean effect nor a volatility increase due to the event. The results clearly indicate that for all sample sizes, due to the correlation, the traditional *t*-statistic, Patell *t*-statistic, and BMP statistic all over-reject the null hypothesis with rejection rates normally 2 to 3 times the nominal rate of 0.05 in the one-tailed test and 2 to 5 times in the two-tailed test. As equations (6) and (11) predict, the over-rejection rates are more pronounced in larger samples, which is also supported by the empirical results of Table 3, where for $n = 50$ the rejection rates for the unadjusted statistics are from 0.105 to 0.156 in the one-tailed test and from 0.208 to 0.248 in the two-tailed test. Contrasting these with respect to the theoretical rejection rates similar to Table 1, the theoretical value for the (unadjusted) Patell statistic in the one-tailed test is $1-\Phi\left(1.96/\sqrt{1+49\times 0.033)}\right)\approx 0.163$ and in two-tailed test $2\times(1-\Phi\left(1.645/\sqrt{1+49\times 0.033}\right)\approx 0.242$, where $\Phi(\cdot)$ is the standard normal distribution function. These theoretical rejection rates compare closely with the simulated empirical rejection rates for the one-tailed and two-tailed tests, which are 0.158 and 0.248, respectively. For the (unadjusted) BMP statistics the corresponding theoretical rejection rates are 0.168 and 0.251, respectively, while the empirical estimates are 0.128 and 0.244. Here we see that the one-tailed theoretical value is to some extent under-estimated.

The remaining columns in Table 3 report the results with event-induced variability. In sum, the overall finding is that the over-rejection gets worse as the variability increases. For example, the Patell statistic rejects the null hypothesis (i.e., no event-induced mean effect) for 50 securities and event-induced variability factor c = 2.0 with probability 0.520, which makes the test useless.

The last three methods (i.e., portfolio, adjusted Patell, and adjusted BMP) in Table 3 are supposed to account for the cross-sectional correlations. In the case of n = 50 securities and no event-induced additional variability, the rejection rates are from 0.040 through 0.064, and hence closely approximate the nominal rate of 0.05. In the smaller samples the estimates are less accurate. For example, with n = 10 securities the rejection rates for the adjusted Patell and adjusted BMP are about 0.10 for the two-sided tests. In sum, except for very small samples, these results indicate that the proposed simple corrections in these statistics remove the bias in the rejection rates.

Table 3 also reports the results when there is event-induced variability but no mean effect. Because the statistics not accounting for cross-sectional correlation (i.e., traditional, unadjusted Patell, and unadjusted BMP) already produce over-rejection even for no event-induced variability, we focus here on the statistics that account for correlation (i.e., portfolio method, adjusted Patell, and adjusted BMP). The last three lines of each of the sample size panels in Table 3 clearly demonstrate that, while the portfolio method and adjusted Patell method account for the correlation effect, they do not capture the event-induced variability. In all cases over-rejection increases as a function of the increased variability. Even for $c = 0.5$ the rejection rate is usually 2 to 3 times the nominal rate. The adjusted BMP statistic is the only one for which in the presence of event-induced variability the estimated rejection rates are reasonably close to the nominal rate of 0.05. If the number of firms in the event study is small, then the rejection rate becomes inaccurate, which obviously is due to the inaccuracy in the variance estimation from a sample of 10 (correlated) observations. Overall, the results in Table 3 indicate that methods not accounting for correlation tend to heavily over-reject the null hypothesis when it is true, and methods accounting for the correlation but not the event-induced variability are vulnerable to the variability increase, thereby resulting in considerable over-rejection of the null hypothesis of no mean effect due to the event. For all but very small sample sizes, the adjusted BMP statistic appears to be the only one that captures both the correlation and the event-induced variability.

Tables 4 through 6 report rejection rates (power) when there are both an event-induced mean effect and a variability effect for the methods accounting for cross-correlation (i.e., portfolio method, adjusted Patell, and adjusted BMP). The power results are not relevant for the traditional and *unadjusted* Patel or BMP because of the over-rejection of the null hypothesis of no mean event effect in the presence of correlation. For the same reason (i.e., over-rejection) the power comparisons are also not relevant for the portfolio method and adjusted Patel in the case of event-induced variability. Consequently, we have not reported them in the tables.

The second column of the Tables 4 through 6 shows the results with no event-induced variance. The adjusted Patell and adjusted BMP methods detect the false null hypothesis at about the same rate. The advantage of the latter is that it is more robust towards event-induced volatility. The simulation results in the second columns (c = 0.0) of Tables 4 through 6 also confirm the well- known fact that the portfolio method is less powerful than the other two methods. Depending on the value of the abnormal return and number of securities, the reduction of power of the portfolio method is from 10 to 60 percent (normally around 30%) compared to the other two methods. The adjusted Patell and adjusted BMP methods are about equally powerful even in small samples, although one would expect the adjusted Patell method to have more power because of the presumably more accurate return variance estimation. The BMP statistic is the only one which accounts for event-induced variance. As the variability increases, the observations become more noisy, which decreases the accuracy of inference. Also, there is a decrease in the power of the BMP test for more volatile abnormal returns.

V. Conclusions

In this paper we have demonstrated via simulation that, 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 event mean effect. We have proposed simple corrections to the popular Patell (1976) and Boehmer, Musumeci, and Poulsen (BMP) (1991) statistics to account for the correlation. Our simulations show that, when there is no event-induced volatility increase, both of these corrected test statistics are approximately equally powerful and reject the null hypothesis at the correct nominal rate when the null hypothesis is true. However, the Patell statistic is sensitive to event-induced volatility and rejects the null hypothesis too often. The adjusted BMP statistic is robust against the event-induced volatility. However, in order to get reliable results with the BMP method, there must be enough firms for the cross-sectional volatility estimation.

References

Bernard, V.L., 1987, Cross-sectional dependence and problems in inference in market-based accounting research, Journal of Accounting Research 25, 1–48.

Boehmer, E., J. Musumeci, and A. B. Poulsen, 1991, Event study methodology under conditions of event induced variance, Journal of Financial Economics 30, 253–272.

Brown, S. J., and J. B. Warner, 1980, Measuring security price performance, Journal of Financial Economics 8, 205–258.

Brown, S. J., and J. B. Warner, 1985, Using daily stock returns: The case of event studies, Journal of Financial Economics 14, 3–31.

Chandra, R., and B. V. Balachandran, 1990, A synthesis of alternative testing procedures for event studies, Contemporary Accounting Research 6, 611–640.

Froot, K. A., 1989, Consistent covariance matrix estimation with cross-sectional dependence and heteroscedasticity in financial data, Journal of Financial and Quantitative Analysis 24, 333–355.

Jaffe, J. F., 1974, The effect of regulation changes on insider trading, The Bell Journal of Economics and Management Science 5, 93–121.

Khotari, S. P., and J. B. Warner, 2005, Econometrics of event studies, in: B. E. Eckbo, ed., Handbooks of Corporate Finance: Empirical Corporate Finance, Chapter 1 (Elsevier/North-Holland, Amsterdam).

Malatesta, P. H., 1986, Measuring abnormal performance: The event parameter approach using joint generalized least squares, Journal of Financial and Quantitative Analysis 21, 27–38.

Patell, J., 1976, Corporate forecasts of earnings per share and stock price behavior: Empirical tests, Journal of Accounting Research 14, 246–276.

Sefcik, S. E., and R. Thompson, 1986, An approach to statistical inference in cross-sectional models with security abnormal returns as dependent variable, Journal of Accounting Research 24, 316–334.

Footnotes

1. If the estimation periods are different for each firm, then $\sigma_j^2 = (m_j - 2)/(m_j - 4)$, where m_j is the number of observations on the estimation period of the jth firm. In this case equation (5) holds only approximately. Nevertheless, if the estimation periods are reasonably long, such that $\sigma_i^2 = (m_i - 2)/(m_i - 4) \approx (m_j - 2)/(m_j - 4) = \sigma_j^2$, then substituting σ_i^2 and σ_j^2 by $\sigma_A^2 = \frac{1}{n}\sum_{j=1}^{n}(m_j - 2)/(m_j - 4)$ [see Patell (1976)] in formula (4) introduces only negligible bias in the standard error of the mean abnormal return.

2. In the more general case where m_{jk} is the length of the estimation period of firm *j* in group *k*, $j = 1, \ldots, n_k$, $k = 1, \ldots, q$, the variances are $\sigma_j^2(k) = (m_{jk} - 2)/(m_{jk} - 4)$. As discussed in footnote 1, if the estimation periods have reasonably many observations, $\sigma_i^2(k) = (m_{ik} - 2)/(m_{ik} - 4) \approx (m_{jk} - 2)/(m_{jk} - 4) = \sigma_j^2(k)$, approximating individual variances $\sigma_i^2(k)$ with the average $\sigma_k^2 = \frac{1}{n_k}\sum_{j=1}^{n_k}(m_{jk} - 2)/(m_{jk} - 4)$, which again introduces only negligible bias into the standard error of the average abnormal return given in equation (12).

Appendix

Here we derive the expected value of cross-sectional variance estimator with non-zero cross-correlations. Suppose that we have *n* cross-sectional abnormal returns $A_1, \ldots, A_n$ that are identically distributed with $E[A_i] = \mu_A$ and $E\left[(A_i - \mu_A)^2\right] = \mathrm{var}(A_i) = \sigma_A^2$ the same for all $i = 1, \ldots, n$, and $\mathrm{cov}(A_i, A_j) = \sigma_{ij}$ (i.e., not independent). Then we can write $\sigma_{ij} = \sigma_A^2 \rho_{ij}$, where ρ_{ij} is the correlation between the abnormal returns *i* and *j*. The standard estimator for σ_A^2 is

(A1) $$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(A_i - \bar{A})^2 ,$$

where $\bar{A} = \frac{1}{n}\sum_{i=1}^{n} A_i$ is the mean abnormal return. Then the expected value of s^2, $E\left[s^2\right]$, is

$E\left[s^2\right] = (1-\bar{\rho})\sigma_A^2$, where $\bar{\rho} = \frac{1}{n(n-1)}\sum_{i=1}^{n}\sum_{j\neq i}\rho_{ij}$ is the average correlation between the returns.

This can be easily seen as follows (c.f. Sefcik and Thompson, 1986). Define

(A2) $$E\left[s^2\right] = \frac{1}{n-1}\sum_{i=1}^{n} E(A_i - \bar{A})^2$$

and

(A3) $$\begin{aligned} E(A_i - \bar{A})^2 &= E\left[\left((A_i - \mu_A) - (\bar{A} - \mu_A)\right)^2\right] \\ &= E(A_i - \mu_A)^2 - 2E(A_i - \mu_A)(\bar{A} - \mu_A) + E(\bar{A} - \mu_A)^2 . \end{aligned}$$

The covariance term in the middle is

$$E(A_i-\mu_A)(\overline{A}-\mu_A)=\frac{1}{n}\sum_{j=1}^{n}E(A_i-\mu_A)(A_j-\mu_A)$$

(A4)

$$=\frac{1}{n}\sum_{j=1}^{n}\sigma_{ij}\;=\frac{1}{n}\sigma_A^2\sum_{j=1}^{n}\rho_{ij}$$

$$=\frac{\sigma_A^2}{n}\left(1+\sum_{\substack{j=1\\ j\neq i}}^{n}\rho_{ij}\right).$$

The last term on the right-hand-side of equation (A3) becomes

$$E(\overline{A}-\mu_A)^2=E\left(\frac{1}{n}\sum_{j=1}^{n}(A_j-\mu_A)\right)^2$$

(A5)

$$=\frac{1}{n^2}\sum_{j=1}^{n}E(A_j-\mu_A)^2+\frac{1}{n^2}\sum_{j=1}^{n}\sum_{\substack{k=1\\ k\neq j}}^{n}E(A_j-\mu_A)(A_k-\mu_A)$$

$$=\frac{1}{n}\sigma_A^2+\frac{n(n-1)}{n^2}\frac{1}{n(n-1)}\sum_{j=1}^{n}\sum_{\substack{k=1\\ k\neq j}}^{n}\sigma_{ij}$$

$$=\frac{1}{n}\sigma_A^2\left(1+(n-1)\overline{\rho}\right).$$

Using equations (A2)–(A5) in equation (A1), we finally get

$$E(s^2)=\frac{1}{n-1}\sum_{i=1}^{n}E(A_i-\overline{A})^2$$

$$=\frac{1}{n-1}\sum_{i=1}^{n}\left(\sigma_A^2-2\frac{\sigma_A^2}{n}\left(1+\sum_{\substack{j=1\\ j\neq i}}^{n}\rho_{ij}\right)+\frac{1}{n}\sigma_A^2(1+(n-1)\overline{\rho})\right)$$

(A6)

$$=\frac{1}{n-1}\left((n\sigma_A^2-2\sigma_A^2\left(1+(n-1)\overline{\rho}\right)+\sigma_A^2\left(1+(n-1)\overline{\rho}\right)\right)$$

$$=\frac{1}{n-1}(n-1)\sigma_A^2(1-\overline{\rho})$$

$$=\sigma_A^2(1-\overline{\rho}).$$

Table 1

True rejection probabilities at the nominal 5 percent level for one-sided and two-sided unadjusted Patell and Boehmer, Musumeci, and Poulsen (BMP) *t*-tests of average abnormal returns when the returns are cross-sectionally correlated.

Number of firms (n)	Average correlation ($\bar{\rho}$)						Average correlation ($\bar{\rho}$)					
	0.00	0.01	0.05	0.10	0.15	0.20	0.00	0.01	0.05	0.10	0.15	0.20
Panel A. Patell *t*-statistic (one-tailed)							Panel B. Patell *t*-statistic (two-tailed)					
5	0.05	0.05	0.07	0.08	0.10	0.11	0.05	0.05	0.07	0.10	0.12	0.14
10	0.05	0.06	0.09	0.12	0.14	0.16	0.05	0.06	0.10	0.16	0.20	0.24
20	0.05	0.07	0.12	0.17	0.20	0.23	0.05	0.07	0.16	0.25	0.32	0.37
30	0.05	0.07	0.15	0.20	0.24	0.26	0.05	0.08	0.21	0.32	0.40	0.45
50	0.05	0.09	0.19	0.25	0.28	0.31	0.05	0.11	0.29	0.42	0.50	0.55
100	0.05	0.12	0.25	0.31	0.34	0.36	0.05	0.16	0.42	0.55	0.62	0.67
200	0.05	0.17	0.31	0.36	0.38	0.40	0.05	0.26	0.55	0.67	0.72	0.76
Panel C. BMP *t*-statistic (one-tailed)							Panel D. BMP *t*-statistic (two-tailed)					
5	0.05	0.05	0.07	0.09	0.12	0.14	0.05	0.06	0.08	0.12	0.15	0.19
10	0.05	0.06	0.09	0.13	0.16	0.19	0.05	0.06	0.11	0.18	0.24	0.29
20	0.05	0.07	0.13	0.18	0.22	0.25	0.05	0.07	0.17	0.27	0.36	0.42
30	0.05	0.07	0.15	0.21	0.26	0.29	0.05	0.09	0.22	0.35	0.43	0.50
50	0.05	0.09	0.19	0.26	0.30	0.33	0.05	0.11	0.30	0.44	0.53	0.59
100	0.05	0.12	0.26	0.32	0.35	0.37	0.05	0.17	0.43	0.57	0.65	0.70
200	0.05	0.17	0.31	0.37	0.39	0.41	0.05	0.26	0.56	0.68	0.74	0.78

Table 2

Sample statistics for event tests from 250 simulated portfolios of n = 50, 30, and 10 securities under no event effects when the residual returns are correlated.

n = 50	Mean	Std.	Min	Max
Traditional *t*-test [Eq. (21)]	-0.063	1.449	-4.646	4.964
Patell test [Eq. (1)]	0.059	1.574	-4.562	6.072
BMP test [Eq. (2)]	-0.019	1.550	-4.722	5.221
Portfolio method [Eq. (22)]	0.003	1.081	-3.528	7.233
Adjusted Patell [Eq. (6)]	0.027	1.022	-3.256	4.213
Adjusted BMP [Eq. (11)]	-0.020	0.977	-3.810	2.747
Average return cross-correlation	0.077	0.050	0.015	0.204
Average residual cross-correlation	0.033	0.025	0.006	0.127
n = 30	Mean	Std.	Min	Max
Traditional *t*-test [Eq. (21)]	-0.144	1.523	-6.057	4.959
Patell test [Eq. (1)]	0.031	1.531	-4.560	6.211
BMP test [Eq. (2)]	-0.061	1.512	-5.430	4.897
Portfolio method [Eq. (22)]	-0.019	1.068	-2.926	4.251
Adjusted Patell [Eq. (6)]	0.025	1.097	-2.774	3.412
Adjusted BMP [Eq. (11)]	-0.041	1.071	-3.470	3.245
Average return cross-correlation	0.078	0.056	0.013	0.274
Average residual cross-correlation	0.036	0.031	0.003	0.179
n = 10	Mean	Std.	Min	Max
Traditional *t*-test [Eq. (21)]	-0.173	1.442	-6.309	2.126
Patell test [Eq. (1)]	-0.047	1.315	-3.906	3.422
BMP test [Eq. (2)]	-0.139	1.648	-9.034	2.591
Portfolio method [Eq. (22)]	0.004	1.064	-3.222	2.560
Adjusted Patell [Eq. (6)]	-0.053	1.139	-3.656	2.247
Adjusted BMP [Eq. (11)]	-0.113	1.347	-6.478	2.518
Average return cross-correlation	0.078	0.061	-0.003	0.261
Average residual cross-correlation	0.036	0.037	-0.008	0.182

Table 3

Average rejection rates at the 5% significance level of the null hypothesis of no mean event effect in the presence of factor 0, 0.5, 1.5, and 2.0 increases in event-induced variance-covariance for 250 random portfolios of n = 50, 30 and 10 securities.[a]

	Event-induced variance-covariance factor c, $\Sigma_c = (1+c)\Sigma$							
	c = 0.0		c = 0.5		c = 1.0		c = 2.0	
Test statistic (n = 50)	1-tail	2-tail	1-tail	2-tail	1-tail	2-tail	1-tail	2-tail
Traditional *t*-test [Eq. (21)]	0.108	0.208	0.116	0.200	0.124	0.204	0.124	0.212
Patell test [Eq. (1)]	0.156	0.248	0.208	0.372	0.256	0.424	0.296	0.520
BMP test [Eq. (2)]	0.128	0.244	0.152	0.252	0.152	0.240	0.148	0.228
Portfolio method [Eq. (22)]	0.040	0.052	0.112	0.104	0.156	0.172	0.216	0.304
Adjusted Patell [Eq. (6)]	0.052	0.064	0.080	0.128	0.120	0.208	0.164	0.280
Adjusted BMP [Eq. (11)]	0.044	0.056	0.044	0.052	0.052	0.048	0.048	0.056
	c = 0.0		c = 0.5		c = 1.0		c = 2.0	
Test statistic (n = 30)	1-tail	2-tail	1-tail	2-tail	1-tail	2-tail	1-tail	2-tail
Traditional *t*-test [Eq. (21)]	0.084	0.188	0.108	0.164	0.112	0.148	0.128	0.152
Patell test [Eq. (1)]	0.104	0.144	0.212	0.336	0.244	0.412	0.284	0.504
BMP test [Eq. (2)]	0.112	0.168	0.128	0.184	0.136	0.176	0.136	0.204
Portfolio method [Eq. (22)]	0.056	0.060	0.120	0.148	0.168	0.236	0.208	0.316
Adjusted Patell [Eq. (6)]	0.064	0.080	0.136	0.144	0.172	0.252	0.224	0.368
Adjusted BMP [Eq. (11)]	0.052	0.060	0.048	0.064	0.060	0.068	0.060	0.072
	c = 0.0		c = 0.5		c = 1.0		c = 2.0	
Test statistic (n = 10)	1-tail	2-tail	1-tail	2-tail	1-tail	2-tail	1-tail	2-tail
Traditional *t*-test [Eq. (21)]	0.084	0.096	0.092	0.120	0.076	0.112	0.132	0.116
Patell test [Eq. (1)]	0.108	0.128	0.164	0.192	0.216	0.300	0.248	0.364
BMP test [Eq. (2)]	0.124	0.180	0.096	0.128	0.100	0.124	0.124	0.136
Portfolio method [Eq. (22)]	0.056	0.080	0.124	0.096	0.148	0.172	0.176	0.288
Adjusted Patell [Eq. (6)]	0.060	0.108	0.092	0.140	0.144	0.208	0.192	0.296
Adjusted BMP [Eq. (11)]	0.080	0.092	0.060	0.088	0.060	0.084	0.072	0.084

[a] As discussed in the text, the variance (covariances) are increased by factor c along lines described in Boehmer et al. (1991), such that the event induces additional variance-covariance is $c\Sigma$, where c is a constant equal to 0, 0.5, 1, or 2 (i.e., the total covariance matrix in the event day 0 is $\Sigma_c = (1+c)\Sigma$, which implies that c = 0 corresponds to a no event-induced variance and c = 2 a variance of 3 times the non-event variance, or $\sqrt{3} \approx 1.73$ times the non-event standard deviation).

Table 4

Average rejection rates for selected test statistics for 250 randomly selected portfolios of n = 50 securities in a one-tailed test at the 5% significance level with 0.5%, 1%, 2%, and 3% abnormal returns and a factor of 0, 0.5, 1.5, and 2.0 increase in event-induced variance-covariance.[a]

	Rejection rates for one-tailed tests at 5% level Event-induced variance-covariance factor c, $\Sigma_c = (1+c)\Sigma$			
Test statistic	c = 0.0	c = 0.5	c = 1.0	c = 2.0
Panel A. Abnormal return 0.5%				
Portfolio method [Eq. (22)]	0.112	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.168	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.132	0.112	0.116	0.096
Panel B. Abnormal return 1.0%				
Portfolio method [Eq. (22)]	0.236	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.404	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.356	0.236	0.192	0.152
Panel C. Abnormal return 2.0%				
Portfolio method [Eq. (22)]	0.572	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.712	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.756	0.548	0.420	0.312
Panel D. Abnormal return 3.0%				
Portfolio method [Eq. (22)]	0.812	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.896	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.888	0.800	0.704	0.528

[a] As discussed in the text, the variance (covariances) are increased by factor c along lines described in Boehmer et al. (1991), such that the event induces additional variance-covariance is $c\Sigma$, where c is a constant equal to 0, 0.5, 1, or 2 (i.e., the total covariance matrix in the event day 0 is $\Sigma_c = (1+c)\Sigma$, which implies that c = 0 corresponds to a no event-induced variance and c = 2 a variance of 3 times the non-event variance, or $\sqrt{3} \approx 1.73$ times the non-event standard deviation). Note that n.a = not applicable, as the portfolio method and the Patell method do not account for event-induced variance-covariance.

Table 5

Average rejection rates for selected test statistics for 250 randomly selected portfolios of n = 30 securities in one-tailed test at the 5% significance level with 0.5%, 1%, 2%, and 3% abnormal returns and a factor of 0, 0.5, 1.5, and 2.0 increase in event-induced variance-covariance.[a]

	Rejection rates for one-tailed tests at 5% level Event-induced variance-covariance factor c, $\Sigma_c = (1+c)\Sigma$			
Test statistic	c = 0.0	C = 0.5	c = 1.0	c = 2.0
Panel A. Abnormal return 0.5%				
Portfolio method [Eq. (22)]	0.096	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.160	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.152	0.132	0.120	0.108
Panel B. Abnormal return 1.0%				
Portfolio method [Eq. (22)]	0.172	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.316	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.284	0.236	0.204	0.156
Panel C. Abnormal return 2.0%				
Portfolio method [Eq. (22)]	0.412	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.620	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.640	0.488	0.376	0.328
Panel D. Abnormal return 3.0%				
Portfolio method [Eq. (22)]	0.708	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.864	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.860	0.724	0.624	0.504

[a] As discussed in the text, the variance (covariances) are increased by factor c along lines described in Boehmer et al. (1991), such that the event induces additional variance-covariance is $c\Sigma$, where c is a constant equal to 0, 0.5, 1, or 2 (i.e., the total covariance matrix in the event day 0 is $\Sigma_c = (1+c)\Sigma$, which implies that c = 0 corresponds to a no event-induced variance and c = 2 a variance of 3 times the non-event variance, or $\sqrt{3} \approx 1.73$ times the non-event standard deviation). Note that n.a = not applicable, as the portfolio method and the Patell method do not account for event-induced variance-covariance.

Table 6

Average rejection rates for selected test statistics for 250 randomly selected portfolios of n = 10 securities in one-tailed test at the 5% significance level with 0.5%, 1%, 2%, and 3% abnormal returns and a factor of 0, 0.5, 1.5, and 2.0 increase in event-induced variance-covariance.

	Rejection rates for one-tailed tests at 5% level Event-induced variance-covariance factor c, $\Sigma_c = (1+c)\Sigma$			
Test statistic	c = 0.0	c = 0.5	c = 1.0	c = 2.0
Panel A. Abnormal return 0.5%				
Portfolio method [Eq. (22)]	0.100	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.104	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.152	0.100	0.100	0.100
Panel B. Abnormal return 1.0%				
Portfolio method [Eq. (22)]	0.172	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.220	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.200	0.180	0.156	0.124
Panel C. Abnormal return 2.0%				
Portfolio method [Eq. (22)]	0.304	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.460	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.420	0.296	0.272	0.220
Panel D. Abnormal return 3.0%				
Portfolio method [Eq. (22)]	0.444	n.a	n.a	n.a
Adjusted Patell [Eq. (6)]	0.612	n.a	n.a	n.a
Adjusted BMP [Eq. (11)]	0.684	0.560	0.432	0.404

[a] As discussed in the text, the variance (covariances) are increased by factor c along lines described in Boehmer et al. (1991), such that the event induces additional variance-covariance is $c\Sigma$, where c is a constant equal to 0, 0.5, 1, or 2 (i.e., the total covariance matrix in the event day 0 is $\Sigma_c = (1+c)\Sigma$, which implies that c = 0 corresponds to a no event-induced variance and c = 2 a variance of 3 times the non-event variance, or $\sqrt{3} \approx 1.73$ times the non-event standard deviation). Note that n.a = not applicable, as the portfolio method and the Patell method do not account for event-induced variance-covariance.