On inference biases in single-firm event-studies:
A new methodology employing a mixture-of-normals model

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ABSTRACT:
Tests of statistical significance of various corporate and industry-wide events usually require an estimate of event-period return volatility. Current event-study methodologies examining events of a single-firm or a portfolio of calendar-date clustered firms assume homoscedasticity of returns during both event and pre-event periods. However, there is strong evidence that the return volatility increases as a result of news. This paper presents a new methodology for estimating the event-period return-volatility in these one-asset studies and provides a tool that would correct the potentially biased inferences and significance tests of numerous previous studies caused by their underestimation of the event volatility. The mixture-of-normals model of asset returns provides a more realistic and economically intuitive alternative to the simple time-series Gaussian model.

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1. Introduction

The event study analysis has become a common tool used in many economic disciplines. Assuming efficiency of markets, the impact of virtually any corporate or macro-economic event can be examined using financial market prices of the affected assets. The change in the market value of rationally priced assets provides the best estimate of both short and long-term effects and thus alleviates the need for a long-term impact study whose results may be influenced by confounding events.

Financial economists have examined the impact of numerous corporate events on stakeholders’ wealth and the extensive list includes mergers and acquisitions, proxy contests and management changes, various security issuances and repurchases, earnings and dividend announcements, and others. In the field of law and economics, stock returns have been used to assess damages in legal liability cases (Mitchell, Netter, 1994) and to determine the impact of

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1 MacKinlay (1997), Lys (1995), and Bruner (1999), among others, provide an overview and recent applications.  
governmental regulation (Schwert, 1981).3 Boehmer, Musumeci and Poulsen (1991) and MacKinlay (1997) provide excellent overviews of the major methodologies.4 This paper is concerned with an important though a less common subset of event-studies that examine an event involving only one firm or a portfolio of event-day clustered assets (an industry index).

Event study inferences and conclusions rest on tests of statistical significance and the usual parametric methodologies require an estimate of the event-period return volatility. Many event studies investigate a cross-section of firms experiencing the same type of event on different calendar days and the tests of statistical significance are based on the cross-sectional estimate of the event-period return volatility. This paper is concerned with methodologies in the other set of applications that examine a single-firm news-event, or an event involving whole industry, or a portfolio of date-clustered firms.5 In these situations, researchers commonly rely on volatility estimates from the pre-event time series of returns and assume normality of abnormal returns during both pre-event and event periods. These assumptions can be summarized by: \( AR_\tau \sim N[0, \sigma^2] \), where \( \tau \in \{t-m, \ldots, t_0, \ldots t+n\} \), and \( t_0 \) is the event day.

However, the event return volatility often increases. For example, Dann’s (1981) stock repurchases study documents that the standard deviation of cross-sectional announcement-day returns is larger by a factor of 3.61 relatively to the standard deviation during the estimation period. Roll (1988) also documents that the return variance is several times larger on news days than on no-news days.

Many authors have previously addressed the hazards of ignoring event-induced increases in return variance. There are several methodologies that appropriately correct for this problem in a multiple-firm event study framework.6 However, numerous event studies investigate only one firm or a portfolio of event-day clustered firms. I claim in this paper that inferences and the statistical significance of abnormal returns in these event studies are suspect and subject to revision. A new methodology is proposed here that alleviates the most obvious

3 The informativeness of results from studies examining regulatory changes and macroeconomic news events has been somewhat limited. The asset prices react only to the incremental or new information revealed to the markets participants. Since regulatory changes are often debated in congress and therefore partially anticipated, event study results reveal only the incremental impact of regulation above the level already impounded in prices.
5 In the case of date-clustered multiple firm event studies, the usual estimates of event-period return volatility utilizing sample firms’ cross-sectional event-day returns are unreliable due to large cross-correlation effects.
inference biases due to a model misspecification and therefore severe underestimation of the event-induced return-volatility. The methodology could be applied in various corporate-finance clinical studies (Lys and Vincent, JFE 1995; Bruner, JFE 1995), industry-wide regulatory policy and anti-trust cases (O’Hara and Shaw, JF 1990; Mullin, RAND 1995), and other “calendar time” event studies (Jaffe, 1974).

Evaluation of the informational event’s impact requires an estimate of the abnormal return, defined as

\[ AR_{i,\tau} = R_{i,\tau} - E(R_{i,\tau} | \Omega_{\tau-1}) \]

where \( AR_{i,\tau} \) and \( R_{i,\tau} \) are the abnormal and actual (ex-post) returns of asset \( i \) on day \( \tau \). \( E(R_{i,\tau} | \Omega_{\tau-1}) \) is the normal (expected) return conditional on the information set \( \Omega_{\tau-1} \). While the issue of measuring this abnormal return correctly is clearly important, it is not addressed here.  

This paper points out several weaknesses in event studies examining the impact of news affecting a single firm or a date-clustered portfolio of firms. The usual significance tests will often fail to reject a hypothesis of a significant event – in the sense that the event-return was indeed due to “new information” and can be safely distinguished from the “trading noise” returns. Also, given the strong evidence of event-day volatility increases, tests of hypotheses of zero abnormal performance will over-reject if the event-day return volatility is estimated using no-news returns or a time-series of pre-event returns. This paper proposes a new methodology for estimating the event-day volatility. The mixture-of-normals model of asset returns provides a more realistic and economically intuitive alternative to the simple Gaussian model.  

Another alternative method to both the Gaussian and the Normals-Mixture models would be to collect a set of returns on similar event days and utilize the cross-sectional variance in hypothesis testing. For various reasons, this benchmark approach may be impractical or impossible in many situations.

This article is organized as follows. The second section presents the model and the third section suggests methodologies for parameter estimation. The fourth section presents some empirical evidence and the last section concludes.

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7 This is the basic question addressed by numerous asset-pricing models. However, since short-period expected returns are close to zero, selection of an asset-pricing model does not seem to have large effect on inferences about abnormal return (see e.g., Brown and Warner, 1980, 1985).
2. The Model and Event-Study Hypothesis Testing

The mixture-of-normals model has been used in several disciplines. Press (1967), Quandt and Ramsey (1978) and Roll (1988) are among the first to use the model in econometric and financial modeling. Kon (1984) and Kim and Kon (1994) examine the statistical properties of returns using the mixtures model and find that it fits ordinary return data better than the stationary Gaussian model.

The suggested mixture-of-normals model acknowledges the fact that the time-series of pre-event returns is a combination (a mixture) of returns on news days and no-news days. Unlike the standard methodologies that assume normality of all pre-event returns, this model relaxes the assumption of homoscedasticity and attempts to separate noise from information events and utilize estimates of general news-days return volatility in hypothesis testing.

Given the findings of event-day volatility increases (see Dann, 1981; Roll, 1988; Boehmer, Musumeci, Poulsen, 1991; among others), a mixture of distributions model is an economically intuitive alternative to the Gaussian model. Implicit in the model is the assumption that all returns on no-news-days are draws from a distribution $Q_1(r)$, and returns on news-days are draws from a distribution $Q_2(r)$, and thus the hypotheses about the event day return can be tested using the estimated distributional properties of $Q(r)$’s.

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8 Quandt and Ramsey (1978) mention several examples of this model’s use in other disciplines, such as engineering (Young and Coraluppi, 1970) and biology (Bhattacharya, 1966).
9 Merton (1976), and Cox and Ross (1976) proposed a similar alternative model in continuous time, the so-called Jump-diffusion model. See also Ball and Torous (1985) and Bates (1991) for estimation and extensions. Nimalendran (1994) uses the jump-diffusion model to estimate the separate effects of information surprises and strategic trading around corporate events. His methodology provides improvements in situations with long event windows, in which case the cumulative abnormal returns pool both the announcement and the trading effects. To study the impact of a specific event, he compares the parameter estimates of the mixed jump-diffusion model during the event period to the estimates from a non-event period. This comparison yields measures of the effects of trading and the effects of incremental information.
10 The pre-event news is possibly and most likely not related to the information event under examination. However, the model assumes that all news event returns are normally distributed. Also, it is unlikely that the firm did not release or the markets did not receive any information during the pre-event period. In that unlikely case of no pre-event news, the normality assumption could be used to test whether our event was a “new information” event.
11 The normality of returns assumption, or Gaussian hypothesis, is due to Bachelier (1900) and Osborne (1959) and is based on the central limit theorem. If the transaction price changes are independent and identically distributed random variables with a finite variance, then the central limit theorem would lead us to believe that returns over intervals such as a day, or a week will be normally distributed. Documented autocorrelations of returns lessens the speed of convergence to normality.
We can model day $t$ abnormal returns of an asset as:

$$x_t = \begin{cases} 
\mu_1 + \sigma_1 \epsilon_{t,1} & \text{in state } P \text{ (no-news days) with probability } "\lambda" \\
\mu_2 + \sigma_2 \epsilon_{t,2} & \text{in state } Q \text{ (news days) with probability } "1-\lambda" 
\end{cases}$$

where $\epsilon_{t,1} \sim N[0,1]$, $\epsilon_{t,2} \sim N[0,1]$, and "~" denotes "is distributed as", and $\sigma_1 < \sigma_2$.

The corresponding unconditional distribution of the abnormal returns is:

$$x_t \sim \lambda N[\mu_1, \sigma_1] + (1-\lambda) N[\mu_2, \sigma_2].$$

There are two possible related hypotheses that can be examined. First, the model allows testing for an existence of a new information event, $E_{t_0}$, on the event day $t_0$. Recognizing the distributional properties of trading-noise returns, the existence can be identified if the following null hypothesis is rejected:

$$H_0 : AR_t | U_t \sim N[0, \sigma_1],$$

where $U_t$ is conditioning on no-news or "noise" events.

This test allows us to differentiate between noise events and new info events that provided some additional information about the firm. In other words, the question that we may address is: Can we reliably distinguish the true news event returns from ordinary noise returns that are primarily due to trading and liquidity pressures, small capitalization changes, and other marginal return aberrations? 12

The most important question, however, is whether the news event had a non-zero impact on corporate value. The hypothesis of no abnormal return ($H_0' : AR_{t_0} = 0$) on the event day $t_0$, can be tested correctly only by recognizing that the event day abnormal return has variance $\sigma_2$:

$$H_0' : AR_t | V_t \sim N[0, \sigma_2],$$

where $V_t$ is the conditioning information that researcher appropriately identified an event.

12 The usual multiple firm cross-sectional studies do not directly test this hypothesis.
3. Estimation of Model Parameters

The mixture-of-normals model has a long history. It appears that the problem of separating the components of a probability density function is one of the oldest estimation problems in the statistical literature. There are several techniques that can be used to estimate parameters of the mixture model: (a) Method of Moments, due to Pearson (1894); (b) Method of Moment Generating Function, due to Quandt and Ramsey (1978); and (c) the Method of Maximum Likelihood. While the Maximum Likelihood estimators are preferred given their well-established properties (see Green, 1996, p. 133), the estimation is not without problems. Quandt and Ramsey (1978) and Hamilton (1991) discuss several issues including the existence of local maxima, unboundedness of the likelihood function and the potential singularity of the matrix of second partial derivatives of the likelihood function.\textsuperscript{13} Hamilton (1991) proposes a quasi-Bayesian approach that alleviates the problem but it requires some subjective judgment in deciding a suitable region for plausible values of variances. In this paper, we propose an alternative two-step approach, in which the method-of-moments estimates are obtained first and subsequently used as starting points for the maximum likelihood estimation.

3.1. The Model’s Density Function and Moments

The density function of the random variable \( x \) introduced by model (3) and its corresponding moment generating function (MGF) are as follows:

\[
f(x) = \frac{\lambda}{\sigma_1 \sqrt{2\pi}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} + \frac{1-\lambda}{\sigma_2 \sqrt{2\pi}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}}, \quad (6)
\]

\[
m(\theta) = \lambda \cdot e^{\mu_1 \bar{\theta} + \frac{1}{2} \sigma_1^2 \bar{\theta}^2} + (1-\lambda) \cdot e^{\mu_2 \bar{\theta} + \frac{1}{2} \sigma_2^2 \bar{\theta}^2}. \quad (7)
\]

The variance (the second central moment) of a mix-normal random variable \( r \) with a density function given by expression (6) can be obtained from the above MGF by differentiating

\textsuperscript{13} More specifically, a singularity arises whenever one of the distributions has a mean exactly equal to one of the observations with no variance. The limit of the likelihood function at any such point is goes to infinity.
twice the natural logarithm of \( m(\theta) \), or a Cumulant Generating Function \( \text{CGF} = \ln m(\theta) \), with respect to \( \theta \) and letting \( \theta \rightarrow 0 \),

\[
\text{Variance}(x) = \frac{\partial^2 \ln(m(\theta))}{\partial \theta^2} \bigg|_{\theta \rightarrow 0} = \lambda(1-\lambda)(\mu_1 - \mu_2)^2 + \lambda \sigma_1^2 + (1-\lambda)\sigma_2^2.
\] (8)

The third central moment, or Skewness = \( \text{E}[x - \text{E}(x)]^3 \), can be expressed as:

\[
\text{Skewness}(x) = \frac{\partial^3 \ln(m(\theta))}{\partial \theta^3} \bigg|_{\theta \rightarrow 0} = \lambda(1-\lambda)(\mu_1 - \mu_2)^3 + \lambda^2(\sigma_1^2 - \sigma_2^2)^2 + 3\lambda(\sigma_1^2 - \sigma_2^2) \bigg].
\] (9)

Similarly, for the fourth central moment, or Kurtosis = \( \text{E}[x - \text{E}(x)]^4 \):

\[
\text{Kurtosis}(x) = \frac{\partial^4 \ln(m(\theta))}{\partial \theta^4} \bigg|_{\theta \rightarrow 0} = \\
= \lambda(1-\lambda)(\mu_1 - \mu_2)^4 + 6(\mu_1 - \mu_2)^4(\sigma_1^2 - \sigma_2^2)^2 + 3\lambda(\mu_1 - \mu_2)^4(\sigma_1^2 - \sigma_2^2)^2 - 6\lambda^2(\mu_1 - \mu_2)^4(\sigma_1^2 - \sigma_2^2) + 6\lambda^2(\mu_1 - \mu_2)^4 \bigg]
\] (10)

3.2. Method of Moments

The Method of Moments was proposed by Pearson (1984) and discussed by Cohen (1967) and Day (1969). The parameters of a density function defined by equation (6) are estimated by equating the sample mean and second through fifth central moments to the corresponding theoretical moments. This provides five equations in five unknowns that can be solved via a ninth-order polynomial for consistent estimators of the five parameters. Recall that the \( k \)-th central moment is defined by:

\[
m_k = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^k , \quad k = 2, 3, 4, 5.
\] (11)

Note that \( m_1 = 0 \) and \( m_2 \) provides an estimate for \( \sigma^2 \). Because \( \bar{x} \) converges in probability to \( \mu \), the central moments converge in distribution to their true theoretical functions. In general,
computing $K$ moments and equating them to these functions provides $K$ equations that can be solved to provide estimates of the $K$ unknown parameters.\(^{14}\)

The solution requires the negative root of the nonic equation:

$$a_9 z^9 + a_8 z^8 + a_7 z^7 + a_6 z^6 + a_5 z^5 + a_4 z^4 +$$
$$+ a_3 z^3 + a_2 z^2 + a_1 z + a_0 = 0,$$  \hspace{1cm} (12)

where:

$$a_9 = 24, \quad a_8 = 0, \quad a_7 = 84 k_4, \quad a_6 = 36 (m_3)^2, \quad a_5 = 90 (k_4)^2 + 72 k_5 m_3,$$

$$a_4 = 444 k_4 (m_3)^2 - 18(k_5)^2, \quad a_3 = 288 (m_3)^4 - 108 m_3 k_4 k_5 + 27 (k_4)^3,$$

$$a_2 = - [63 (k_4)^2 + 73 m_3 k_5] (m_3)^2, \quad a_1 = 96 (m_3)^4 k_4, \quad a_0 = - 24 (m_3)^6,$$

where $m^i$ denotes the $i$-th central sample moments and $k_j$ is the $j$-th sample cumulant; e.g., $k_4 = m_4 - 3 (m_2)^2$, and $k_5 = m_5 - 10 m_2 m_3$.

It can be further shown (Cohen, 1967) that if we define the differences:

$$d_1 = \mu_1 - E(x), \quad \text{and} \quad d_2 = \mu_2 - E(x)$$  \hspace{1cm} (13)

and if $\hat{z}$ is the negative root which solves equation \((12)\), and if $r$ is defined by:

$$r = \frac{- 8 m_3 \hat{z}^3 + 3 k_5 \hat{z}^2 + 6 m_3 k_4 \hat{z} + 2 m_3^3}{\hat{z} (2 \hat{z}^3 + 3 k_4 \hat{z} + 4 m_3^2)},$$  \hspace{1cm} (14)

then we obtain as estimates of $d_1$ and $d_2$:

$$\hat{d}_1 = \frac{1}{2} \left( r - \sqrt{r^2 - 4 \hat{z}^2} \right), \quad \text{and} \quad \hat{d}_2 = \frac{1}{2} \left( r + \sqrt{r^2 - 4 \hat{z}^2} \right).$$  \hspace{1cm} (15)

\(^{14}\) Kumar, Nicklin and Paulson (1979) note that the method of moments does not provide estimators which are statistically appealing since the consideration of only the first five moments or cumulants may result in a considerable loss of information. Moreover, the higher the order of the moment, the greater the sampling variability. Though any sequence of moments (even fractional, e.g., non-integer) carries information about the parameters in question and can be used to solve for parameters, these procedures are more complicated than solving a nonic equation.
From the above results we obtain the estimates of the vector \( \{ \lambda, \mu_1, \sigma_1, \mu_2, \sigma_2 \} \):

\[
\hat{\mu}_1 = \hat{d}_1 + \bar{x}, \\
\hat{\mu}_2 = \hat{d}_2 + \bar{x}, \\
\hat{\sigma}_1^2 = \frac{1}{3} \hat{d}_1 (2r - m_3 / \hat{\sigma}) + m_2 - \hat{d}_1^2, \\
\hat{\sigma}_2^2 = \frac{1}{3} \hat{d}_2 (2r - m_3 / \hat{\sigma}) + m_2 - \hat{d}_2^2, \\
\hat{\lambda} = \hat{d}_2 / (\hat{d}_2 - \hat{d}_1),
\]  

(16)

where \( \bar{x} \) is the sample mean, and \( \lambda \) is the mixture coefficient. Though it is known that the sample variances of high-order moment estimates are very large (Kendall, Stuart and Ord, 1998) and therefore affect the variances of parameters, the estimated parameters can be used as starting points in ML estimation which is known to have serious difficulties.

### 3.3 Method of Maximum Likelihood

Properties of ML estimators are well established (see Green, 1997, page 133). ML estimators are consistent, asymptotically normal, efficient and invariant to re-parameterization. It is possible to estimate the parameters of a normal-mixture distribution defined by (6) by maximizing the likelihood function:

\[
f(X, \gamma) = \prod_{i=1}^{n} f(x_i, \gamma) = L(\gamma \mid X),
\]  

(17)

where \( X \) denotes the sample vector \( \{x_i\}_{i=1,\ldots,n} \). Equivalently, it is possible to maximize the log of the likelihood function, which is usually simpler in practice.
The necessary first-order condition for maximizing $ln \, L(\gamma, X)$ is:

$$\frac{\partial \ln L(\gamma, X)}{\partial \gamma_i} = 0,$$

where $\gamma$ is the parameter vector $[\lambda, \mu_1, \sigma_1, \mu_2, \sigma_2]$.  

(18)

As mentioned before, there are several problems with the ML estimation for a mixture of distributions model, but the use of method-of-moments estimates as starting points in a maximum likelihood surface search provides satisfactory values, and avoids subjectivity required by Hamilton’s (1991) approach.

4. An Empirical Test

To demonstrate the potential for a single firm event-study model mis-specification, I examine abnormal daily returns of General Electric (GE) from January 1, 2000 till May 1, 2001. The sample contains 347 daily abnormal returns whose main characteristics are described in Table 1. Abnormal returns are calculated as market-adjusted simple returns, and S&P500 is used as a market proxy:\textsuperscript{15}

$$AR_{GE,t} = R_{GE,t} - R_{S&P500,t}.$$  

(19)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>$AR_{GE}$</td>
<td>0.048%</td>
<td>1.81%</td>
<td>0.046%</td>
<td>1.26%</td>
<td>-6.66%</td>
<td>6.99%</td>
</tr>
</tbody>
</table>

Table 1:
Sample description. Daily abnormal returns of GE stock, January 1\textsuperscript{st}, 2000 to May 1\textsuperscript{st}, 2001; 347 trading days.

The standard methodology (using time series Gaussian model) would lead us to believe that GE’s abnormal returns are distributed as $AR_{GE,t} \sim N(\, 0.048\%, \, 1.81\%).$ The estimated standard deviation of GE’s abnormal returns during the sample period is 1.81%. This means that researchers using the usual methodology to test for abnormal performance would not be able to distinguish event days with about 3.6% (circa 2 sigma t-test) abnormal returns from no-news events. On the other hand, they would interpret all events with higher than 3.6% abnormal returns as significant.

\textsuperscript{15} Within the CAPM framework, market-adjusted returns are consistent with an assumption that $\beta=1$. This seems to be reasonable for GE returns.
returns as significant news events, e.g. they would reject the null hypothesis of zero abnormal performance.

However, as argued before, this inference would be biased because news increases event-day return volatility. Using the methodology described in Section 3, I estimate the parameters of the mixture-of-normals model specified by expressions (2) and (3) above. Table 2 provides the parameter estimates of this model. Exhibit 1 shows the distribution of GE’s abnormal returns and normal fit (dashed line) as well as mix-normal (thick full line) fit.

Table 2:

<table>
<thead>
<tr>
<th></th>
<th>( \lambda )</th>
<th>( \mu_1 )</th>
<th>( \sigma_1 )</th>
<th>( \mu_2 )</th>
<th>( \sigma_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{AR}_{GE,t} )</td>
<td>0.73</td>
<td>0.0178%</td>
<td>1.399%</td>
<td>0.1305%</td>
<td>2.62%</td>
</tr>
</tbody>
</table>

The mixture-of-normal model suggests that GE’s abnormal returns are distributed as follows: \( \text{AR}_{GE,t} \sim 0.73 \ N[0.0178\% , 1.4\%] + 0.27 \ N[0.13\% , 2.62\%] \).

The first part of this distribution can be interpreted as the distribution of no-news day returns and the second part as the distribution of returns on news event days. Therefore, hypotheses of zero abnormal performance should not be rejected unless event day abnormal returns exceed 5.2\% (about 2-sigma events). On the other hand, all days with returns above 2.8\% can be regarded as being significantly different from “noise” (no-event) returns.

Exhibit 1:
Distribution and fit of GE’s abnormal returns, January 1\textsuperscript{st}, 2000 to May 1\textsuperscript{st}, 2001.
5. Conclusions

Current event study methodologies examining a single-firm event or a macroeconomic news event involving a portfolio of calendar-date clustered firms assume homoscedasticity of returns during both event and pre-event periods. However, there is strong evidence that the return volatility increases as a result of news. This paper presents a new methodology for estimating the event-day return variance that corrects the potential inference biases caused by the underestimation of the event-induced return volatility. The mixture-of-normals model of asset returns provides a more realistic and economically intuitive alternative to the Gaussian model. The estimated mixture-of-normals model parameters for a sample of GE’s abnormal returns show that the potential for under-estimation of event-induced volatility is sizeable. The methodology could be applied in various corporate-finance clinical studies (Lys and Vincent, JFE 1995; Bruner, JFE 1995), industry-wide regulatory policy and anti-trust cases (O’Hara and Shaw, JF 1990; Mullin, RAND 1995), and other “calendar time” event studies (Jaffe, JBus 1974). Model misspecification can potentially lead to erroneous inferences such as mis-identification of event days with zero abnormal performance.
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