Multi-Country Event Study Methods

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Which event study methods are best in non-U.S. multi-country samples? Nonparametric tests, especially the rank and generalized sign, are better specified and more powerful than common parametric tests, especially in multi-day windows. The generalized sign test is the best statistic but must be applied to buy-and-hold, not cumulative, abnormal returns, for correct specification. Market-adjusted and market-model methods with local market indexes, without conversion to a common currency, work well. The results are robust in multiple scenarios, e.g. concentrated markets, highly non-normal markets and market-moving events. Applying the tests that perform best in simulation to merger announcements produces reasonable results.

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Abstract

Which event study methods are best in non-U.S. multi-country samples? Nonparametric tests, especially the rank and generalized sign, are better specified and more powerful than common parametric tests, especially in multi-day windows. The generalized sign test is the best statistic but must be applied to buy-and-hold, not cumulative, abnormal returns, for correct specification. Market-adjusted and market-model methods with local market indexes, without conversion to a common currency, work well. The results are robust in multiple scenarios, e.g. concentrated markets, highly non-normal markets and market-moving events. Applying the tests that perform best in simulation to merger announcements produces reasonable results.

1. Introduction

Researchers use event-study methods to gauge the effects of information arrival on stock prices. The investigator tests the hypothesis that an information release affects the value of the stock, on average, across firms with similar information arrival. A rich methodological literature analyzes the performance of event-study methods. Most of the literature to date focuses on U.S. data, but the use of event studies with non-U.S. data is growing rapidly.

Stock markets differ on many dimensions. For example, stock markets differ in size, liquidity, trading volume, market-making mechanisms, accounting standards, securities regulation, investor protection, ownership concentration and corporate governance. Market characteristics can affect the statistical properties of stock returns. Compared to U.S. data, commonly used test statistics may be less powerful and may be biased toward or against rejection of the null hypothesis. When samples combine stocks from multiple, diverse national markets, the applicability of evidence on test performance drawn from single-market samples is an empirical question.

We analyze the performance of several event-study statistical tests using the market-adjusted and market-model benchmark methods in non-U.S. multi-country samples. Return distributions in such samples are severely non-normal, even at the portfolio level. Consistent with non-normality, we find that two nonparametric tests, the generalized sign (Cowan, 1992) and rank (Corrado, 1989) tests, are better specified and more powerful in simulation than commonly used parametric tests. For testing the stock-price reaction on a known event date, most tests are well specified but the nonparametric tests are more powerful. When testing a window of several days around the event, the generalized sign test must be applied to buy-and-hold abnormal returns; its specification is poor when applied to cumulative abnormal returns. The generalized sign test applied to buy-and-hold abnormal returns is the most powerful test for multi-day windows. The rank test is correctly specified to conservative in random samples and has good power to detect an abnormal return on a known event date, but is less powerful for detecting relatively small abnormal returns in multi-day windows. A third nonparametric test, the jackknife test, is frequently misspecified.

Generally, the above conclusions hold in the presence of a variance increase on the event date. We also find the favorable performance of the rank and generalized sign tests to be robust to samples that are clustered by country or drawn from the ten most concentrated national markets or ten most non-normally distributed markets by subperiod. We consider the ability of these tests to detect abnormal returns when the affected securities constitute a sufficiently large fraction of their respective local exchanges that they are potential "market movers," that is, the individual stock-price effects of their information arrivals are reflected in the market index. The rank and generalized sign tests continue to exhibit correct specification and good power under such conditions.

We also consider aspects of multi-country event-study design other than test-statistic selection. First, many markets are characterized by high frequencies of missing returns due to non-trading. Our results show that treating missing returns as zero returns, sometimes called the "lumped returns" procedure, produces similar event-study test performance to the more standard "trade to trade" method, which involves omitting missing-price days from calculations while reflecting the cumulative market-index returns from those days on subsequent non-missing price days. Second, our results indicate that the use of a local market index, without incorporating an international or U.S. index, is sufficient to produce well-specified and powerful tests of average stock-price effects. Third, the results suggest that for the types of stock-price reaction tests that we investigate, there is no need to convert returns from different markets into a common currency.

We also apply the rank and generalized sign tests to multi-country samples of acquiring and target firms involved in actual merger and acquisition announcements. The tests reject the null hypothesis for targets but not acquirers, consistent with the merger and acquisition literature. The main point of this exercise is that the use of multi-country samples does not appear to impair the researcher's ability to draw inferences from abnormal returns in practice, provided that well-specified and powerful test statistics are used.

2. Recent multi-country event studies

Table 1 summarizes 16 recently published articles that apply event-study methods to multi-country samples. We do not claim this is an exhaustive list, nor is our intention to criticize specific articles. Our purpose is to survey current practice to motivate and provide context for our simulation work, and to make recommendations for future research.

[Insert Table 1 here.]

The 16 articles tend to report relatively simple methods for identifying a benchmark or "normal" return. Eight use only a single-index market model, five report market-adjusted returns (where the market index return is the proxy for a normal stock return), two report both the market model and market-adjusted returns and one reports a seemingly unrelated regressions approach. All but two studies use local market index returns; one uses a global index and one uses a regional index.

For testing whether abnormal returns differ from zero, eight studies report only a parametric test, six report both parametric and nonparametric tests, one reports significance levels but does not indicate how they are obtained and one reports only point estimates without a test. Of the 14 using a parametric test, six report a test that incorporates the time-series standard deviation of the sample mean return from a separate estimation period, designated the "crude dependence adjustment" (CDA) by Brown and Warner (1980, 1985). Two studies report a parametric test based on standardized abnormal returns, introduced by Patell (1976) and also derived by Mikkelson and Partch (1986). Five papers report the use of a "t-test" without further explanation; we surmise that this could be either a simple cross-sectional test or one specific to the event-study literature. Of the six that report non-parametric tests, three use the Wilcoxon signed rank test, one uses the rank test introduced for event studies by Corrado (1989), one uses the generalized sign test that allows the fraction of positive returns under the null to be different from 0.5 as determined by estimation-period data (Cowan, 1990) and one uses a bootstrapping procedure. All 16 studies obtain non-U.S. return data from Thomson Reuters Datastream.

3. Data and methods

3.1 Data

We use Datastream to obtain daily data for over 50,000 non-U.S. stocks over 1988–2006. We download prices, dividends and volume for stock codes tracked by Cowan Research, L.C. over several years, based on numerous lists compiled by Datastream. The tracking procedure attempts to track every equity security with Datastream data, including dead (delisted) equities. We limit the initial data set to equities meeting the following criteria.

- The beginning date of data on Datastream is not missing and is before July 1, 2004. This criterion limits the data set to equities that potentially have adequate data for the random selection and simulation procedures.
- A time series of prices for a minimum of 300 consecutive trading days is available in 1988–2006. In making this determination, we do not exclude missing prices. However, the criterion requires some judgment, because Datastream does not report an ending date for an individual security. We designate the last date of a reported non-missing price as the ending date for each security. If fewer than 300 trading days exist between the reported beginning date or the first trading day of 1988, whichever is later, and the inferred ending date, we exclude the security.
- The security name record on Datastream does not include one of the codes (listed in Appendix A) that indicate the security is not an ordinary share (common stock in U.S. terms).
- The security is not traded in the U.S.

We also download the Datastream Global total market index corresponding to each equity issue. This is a series of value-weighted national market indexes in local currency that is also called the "level one" Datastream Global index series. Despite their labeling by Datastream as "total market" indexes, Datastream's online help indicates that the level one indexes "do not include all companies in a market" but consist of "the most important companies by market value."

Because different markets are characterized by different trading frequencies, excluding stocks from the simulations based on a moderate absolute number of non-missing returns regardless of market could result in an overrepresentation of thickly traded stocks and stocks in more heavily traded markets. Therefore, we adopt what we believe to be a conservative approach to excluding stocks due to missing returns. First, in constructing the data set from which we draw simulation samples, we exclude stocks that are in the quartile of each market in each year having the lowest frequency of non-missing returns (in effect, the quartile of the market with the fewest trading days in that year). Second, we require each randomly selected security-event to have a minimum of 24 non-missing stock-return (and corresponding market-index return) observations in its 251-day estimation period (further described in section 3.3).

3.2 Return and abnormal return calculations

3.2.1 Returns

We calculate stock returns from prices and dividends to avoid the rounding problem with Datastream return indexes reported by Ince and Porter (2006). Each daily stock return is calculated from the previous day with a non-missing price to the current day, including dividends. We use the Datastream price data type P, which the database delivers already adjusted for stock splits and other capital events.

To take into account different methods of handling non-trading of stocks, we calculate both trade-to-trade and lumped daily returns (Maynes and Rumsey, 1993). Trade-to-trade returns are simply the calculated returns from non-missing price days; the return on a missing price day is missing. For a stock with a missing price, the corresponding market-index return is added to the next non-missing price day's index return for trade-to-trade abnormal return calculation. Lumped returns consist of trade-to-trade returns on non-missing price days and zero on missing price days. The market-index return adjustment for missing trade-to-trade returns is not performed for lumped returns because the lumped return calculation produces no missing returns. Maynes and Rumsey argue that lumped returns, by increasing the number of return observations, can improve the efficiency of estimators and test statistics used in event studies.

3.2.2 Abnormal returns

Market-adjusted abnormal returns, or simply market-adjusted returns, are

$$u_{it} = R_{it} - R_{mt}, \tag{1}$$

where R_{it} is the return of security i on day t, and R_{mt} is the local value-weighted market index return.[1] Market model abnormal returns are

$$u_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}), \tag{2}$$

where $\hat{\alpha}$ and $\hat{\beta}_i$ are ordinary least squares estimates of market model parameters.

Researchers using event-study methods commonly examine multi-day windows to account for potential imprecision in dating the event itself, the availability of information about it to market participants or the speed of the event's effects on security prices. Multi-day windows may be particularly useful in multi-country samples where time zones and holidays affect the dates on which information can be impounded in stock prices. We examine windows of three and 11 trading days centered on the event date. Initially, we consider primarily holding-period cumulative abnormal returns. The cumulative abnormal return for stock i over the event window is

$$CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} u_{it} \tag{3}$$

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[1] The Datastream Global level one index for each market is value (capitalization) weighted; the database provides no equal weighted version. Few studies address the differences between equal and value weighted indexes for event studies. Campbell and Wasley (1993) find the equal weighted CRSP Nasdaq market index is preferred for event study tests with nonparametric statistics. Canina, Michaely, Thaler and Wormack (1998) report that compounding an equal-weighted index over a long horizon can produce surprisingly large biases in measured abnormal returns.

The cumulative average abnormal return for a sample of N stocks is

$$CAAR\left(T_1,T_2\right)=\frac{1}{N}\sum_{i=1}^{N}CAR_i\left(T_1,T_2\right). \tag{4}$$

Some of the simulations also use buy-and-hold abnormal returns (BHAR). The buy-and-hold market-adjusted return for stock i over the event window is

$$BHAR_i\left(T_1,T_2\right)=\prod_{t=T_1}^{T_2}\left(1+R_{it}\right)-\prod_{t=T_1}^{T_2}\left(1+R_{mt}\right) \tag{5}$$

where R_{mt} is the local market return on day t for market-adjusted returns. The buy-and-hold market-model abnormal return is

$$BHAR_i\left(T_1,T_2\right)=\prod_{t=T_1}^{T_2}\left(1+R_{it}\right)-\left[\prod_{t=T_1}^{T_2}\left(1+\alpha_i\right)+\prod_{t=T_1}^{T_2}\left(1+\beta_i R_{mt}\right)-1\right]. \tag{6}$$

3.3 Simulation method

We adopt the simulation approach pioneered by Brown and Warner (1980, 1985) and used in several subsequent methodological studies (e.g., Campbell and Wasley, 1993, 1996; Corrado, 1989; Corrado and Truong, 2008; Cowan, 1992; Cowan and Sergeant, 1996; and Savickas, 2003). The approach resembles a Monte Carlo simulation, but instead of drawing from a theoretical probability distribution, observations are randomly drawn from actual data. To simulate an event study, the researcher randomly selects a stock and an event date, and repeats the process to create multiple samples. Historical stock and market-index return data for the randomly selected security-events are used to estimate relevant parameters and calculate test statistics. To evaluate the ability of a test to detect a stock-price reaction to an event, the researcher artificially induces, or "seeds", an abnormal return by adding a constant to the actual return. Repetition across multiple samples provides a picture of the specification and power of the test statistic.

In this study, we create 1,000 samples, each containing 100 security-events. To allow for losses of randomly selected security-events due to inadequate data, we initially select 250,000 stocks with replacement using a uniform distribution generator. Each stock in our data set thus has an equal probability of being selected on each draw regardless of its market or the length of its listing period (subject to the minimum listing period requirement described in section 3.1). For each stock selection, we randomly draw an event date (day zero) using a uniform distribution over the period from 259 trading days after the first recorded trading day for the stock to 35 days before the last recorded trading day.[2]

Trading days –256 through –6 are designated as the estimation period for market model parameters, standard deviations, fractions of abnormal returns with positive or negative signs, and ranks. A security-event that does not meet this criterion is dropped from the sample and replaced with the next random selection until we have 1,000 samples of 100. Trading days –5 through +5 are designated as the event period, from which we separately examine day zero and three-day and 11-day windows centered on day zero. To simulate abnormal returns, we add the following seeds to the event-day return: 0.05, –0.03, –0.01, –0.005, 0, 0.005, 0.01, 0.03, and 0.05.

3.4 Event-study tests

We examine five alternative test statistics from the literature. Two are parametric and three are nonparametric statistical tests. The first parametric test is the Patell (1976) Z statistic. In the finance literature, other studies are frequently cited for an identical or nearly identical test, particularly Dodd and Warner (1983) and Mikkelson and Partch

[2] The specific choices of 259 and 35 days are arbitrary, but motivated by our interest in avoiding the inclusion of the initial and final trading days in the estimation and event periods and allowing the option of using longer event windows.

(1986). Brown and Warner (1980, 1985) point out that a distinguishing feature of the test is that it assumes independence of returns across security-events. This assumption can improve power but also can lead to misspecification when departures from the assumption are substantial. The Patell statistic is calculated using standardized abnormal returns, and therefore the procedure is sometimes referred to as a standardized test. Campbell and Wasley (1993) report that the test rejects a true null hypothesis too often with Nasdaq samples due to the frequency of zero returns and the non-normality of Nasdaq returns, particularly lower priced and less liquid securities. Maynes and Rumsey (1993) report a similar misspecification of the test using the most thinly traded one-third of Toronto Stock Exchange (TSE) stocks. Cowan and Sergeant (1996) report the excessive rejections in Nasdaq samples in upper-tailed but not lower-tailed tests. The Patell test statistic for day t is

$$Z_t = N^{-1/2} \sum_{i=1}^{N} \left(\frac{M_i - 2}{M_i - 4} \right)^{-1/2} \frac{u_{it}}{s_{it}}, \tag{7}$$

where u_{it} is the estimated abnormal return, N is the number of securities in the sample on day t, M_i is the number of estimation-period non-missing returns in security-event i's estimation period and s_{it} is the estimated standard deviation of security-event i's day t abnormal return, further defined below. Under the null hypothesis, if event-date standardized abnormal returns are independent across security-events, this statistic converges to unit normal.

For market-model abnormal returns, the estimated variance of each u_{it} is

$$s_{it} = s_{i(est)} \left[1 + \frac{1}{M_i} + \frac{(R_{mt} - \bar{R}_m)^2}{\sum_{t=-256}^{-6} (R_{mt} - \bar{R}_m)^2} \right]^{1/2} \tag{8}$$

where $\bar{R}_m$ is the mean market-index return from the estimation period and

$$s_{i(est)} = \sqrt{\frac{1}{M_i - 1} \sum_{t=-256}^{-6} (u_{it} - \bar{u}_i)^2} \; ; \tag{8}$$

$\bar{u}_i = (1/M_i) \sum_{t=-256}^{-6} u_{it}$.

For three- and 11-day event windows the Patell test statistic is:

$$Z_t = \left[(T_2 - T_1 + 1) N \right]^{-1/2} \sum_{i=1}^{N} \left[\left(\frac{M_i - 2}{M_i - 4} \right)^{-1/2} \sum_{t=T_1}^{T_2} \frac{u_{it}}{s_{it}} \right]. \qquad {}^{3}(10)$$

The second parametric test is the portfolio time-series standard deviation test; Brown and Warner (1980, 1985) refer to the test as incorporating a “crude dependence adjustment.” That is, the test compensates for potential dependence of returns across security-events by estimating the standard deviation using the time series of sample (portfolio) mean returns from the estimation period. The test statistic for day zero is

$$t_{CDA} = \bar{u}_t / s(\bar{u}_t), \tag{13}$$

where $\bar{u}_t$ is the equal-weighted portfolio mean abnormal return on day *t*, i.e.,

$\bar{u}_t = (1/N) \sum_{i=1}^{N} u_{it}$, and the standard deviation of $\bar{u}_t$ is

[3] Mikkelson and Partch (1988b) (published as a correction to Mikkelson and Partch, 1988a) present a version of the Patell test corrected for the serial correlation that results from basing each abnormal return in a multi-day window on the same market-model parameter estimates. Re-running the Patell test simulations in this paper using the correction does not produce materially different results.

$$s(\bar{u}_t) = \sqrt{(1/250)\sum_{t=-256}^{-6} (\bar{u}_t - \bar{\bar{u}})^2}\ , \qquad (14)$$

where $\bar{\bar{u}} = (1/251)\sum_{t=-256}^{-6} \bar{u}_t$. The standard deviation estimated using portfolio-level time-series data from the estimation period automatically reflects all the pairwise correlations between abnormal returns, thereby addressing cross-sectional dependence. If the u_{it} are normal, independent and identically distributed, this test statistic is distributed Student t, and is approximately unit normal under the null hypothesis. For the three and 11-day event windows the test statistic is:

$$t_{CDA(T_1,T_2)} = CAAR(T_1,T_2) / \sqrt{(T_2 - T_1)} \times s(\bar{u}_t). \qquad (15)$$

Boehmer, Musumeci and Poulsen (1991) develop a variance-change corrected version of the Patell test that they call the standardized cross-sectional test. They report simulation evidence that the test is robust to variance increases. We include this test only when we simulate a variance increase on day zero. The standardized cross-sectional test statistic for day *t* is

$$Z_t = \frac{\left(\frac{N(T-2)}{T-4}\right)^{-1/2} \sum_{i=1}^{N} (u_{it} / s_i)}{s_t} \qquad (16)$$

where s_t is the cross-sectional standard deviation of abnormal returns on day *t*,

$$\sqrt{[1/(N-1)]\sum_{i=1}^{N} (u_{it} - \bar{u}_t)^2}\ . \qquad (17)$$

and $\bar{u}_t$ is the mean portfolio abnormal return on *t*. For multi-day windows, the test statistic is based on the standardized cumulative abnormal return,

$$SCAR_j(T_1,T_2) = CAR_j(T_1,T_2) \big/ s_{CAR_j(T_1,T_2)}\ , \qquad (18)$$

where for market-adjusted returns, the estimated standard deviation of each $CAR_j(T_1,T_2)$ is

$$s_{CARj(T_1,T_2)} = W_j^{1/2} s_j \tag{11}$$

where W_j is the number of non-missing returns in the three- and 11-day event windows. For a market-model CAR, the estimated standard deviation is

$$s_{CAR_j(T_1,T_2)} = s_j \left[W_j + \frac{W_j^2}{M_j} + \frac{\sum_{t=T_1}^{T_2} (R_{mt} - W_j \bar{R}_m)^2}{\sum_{t=-256}^{-6} (R_{mt} - \bar{R}_m)^2} \right]^{1/2} . \tag{12}$$

The standardized cross-sectional statistic for the window is

$$Z_t = \frac{\sum_{j=1}^{N} SCAR_j(T_1,T_2)}{\sqrt{N} s_{SCAR_\bullet}}, \tag{19}$$

where

$$s_{SCAR_\bullet} = \left[\frac{1}{N-1} \left(\sum_{j=1}^{N} SCAR_j(T_1,T_2) - \frac{1}{N} \sum_{i=1}^{N} SCAR_i(T_1,T_2) \right) \right]^{1/2} . \tag{20}$$

The first nonparametric test is the generalized sign test analyzed by Cowan (1992) and avoids the assumption of normal return distributions. The null hypothesis of the generalized sign test is that the fraction of day zero abnormal returns having a particular sign is equal to the fraction in the estimation period. For negative seeded abnormal returns, we test the null of a non-negative sign; for positive seeds, we test the null of a non-positive sign. Cowan reports the test to be well specified and powerful in general samples from NYSE-AMEX and Nasdaq stocks; given the sample period, the Nasdaq sample is likely to be thinly traded on average. Corrado and Truong (2008) also report that the generalized sign test performs well in simulations of single-market samples for 11 Asia-Pacific stock markets.

The number expected is based on the fraction of positive abnormal returns for a portfolio of *N* securities ($\hat{p}$) in the 251-day estimation period,

$$\hat{p} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{M_i}\sum_{t=-256}^{-6} S_{it} \tag{21}$$

where $M_i \le 251$ is the number of non-missing returns in the estimation period for security-event *i* and

$$S_{it} = \begin{cases} 1 & \text{if } u_{it} > 0 \\ 0 & \text{otherwise} \end{cases}. \tag{22}$$

The test statistic uses the normal approximation of a binomial distribution with parameter $\hat{p}$. Define *w* as the number of stocks in the event window for which the abnormal return, the cumulative abnormal return (CAR) or the buy-and-hold return (BHAR) is positive. The generalized sign test statistic is

$$Z_G = \frac{w - N\hat{p}}{[N\hat{p}(1-\hat{p})]^{1/2}}. \tag{23}$$

The second nonparametric test is Corrado's (1989) rank test. It transforms each security's time series of abnormal returns into their respective ranks and hence is not dependent on an assumption of normality of returns. The rank statistic for day zero is

$$t_{rank} = \left[\left(\frac{1}{N_0}\sum_{i=1}^{N_0} k_{i0}\right) - \bar{k}\right] \Big/ s_k , \tag{24}$$

where k_{io} is the rank of security-event *i*'s day zero abnormal return in security-event *i*'s combined 251-day estimation period and 11-day event period time series, $\bar{k}$ is the expected rank defined below and s_k is the time-series standard deviation of the sample mean abnormal return rank.

Corrado (1989) does not allow for missing observations in the return time series, and therefore assumes the expected rank to be constant across securities. For example, with a 262-day combined estimation and event period and the lowest rank being one, the mean rank would be the mean of the first 262 positive integers, 131.5. We do not follow this assumption, but instead allow for missing returns as follows. We rank each security-event's non-missing returns with the lowest rank being zero. If there are missing returns, we transform the security-event's raw ranks to a scale of 0–261 by multiplying the raw rank by a scaling factor (262 divided by one plus the number of non-missing returns) and truncating to the integer part. The expected rank is the empirical mean of the transformed ranks, $\bar{k} = \frac{1}{261} \sum_{j=-256}^{+5} \frac{1}{N_t} \sum_{i=1}^{N_t} k_{it}$. The standard deviation, s_k, is estimated at the portfolio level from the combined 251-day estimation and 11-day event periods as

$$s_k = \left\{ \frac{1}{261} \sum_{j=-256}^{+5} \left[\left(\frac{1}{N_t} \sum_{i=1}^{N_t} k_{it} \right) - \bar{k} \right]^2 \right\}^{1/2}. \qquad (25)$$

The rank statistic converges to unit normal as the number of securities in the portfolio increases (Corrado, 1989).

Corrado (1989) applies the rank test only to day zero. Similar to Cowan (1992), we apply the rank test to a multi-day window CAAR by substituting security-event *i*'s mean rank across the three or 11 days that make up the window, in place of k_{io} in equation (24), and dividing s_k by the square root of three or 11.

Corrado (1989) reports the rank test to be well specified and powerful for New York Stock Exchange (NYSE) stocks. Campbell and Wasley (1993) find similar results for this test statistic for Nasdaq stocks even in small portfolios and infrequently traded low priced securities. Corrado and Truong (2008) find similar results for single-market Asia-Pacific samples.

The third nonparametric test is the jackknife test of Giaccotto and Sfiridis (1996). They report that the test is well specified and powerful when the variance of return increases around the event. In the statistics literature, a jackknife estimator combines K estimates from a data set of size K, where each estimate is computed with a different observation omitted (e.g., Efron and Tibshirani, 1993). Giaccotto and Sfiridis apply the jackknife to event studies, focusing on a standardized abnormal return where the standard deviation is estimated from the event period. Following Giaccotto and Sfiridis, the statistic for each security-event is the standardized abnormal return on day zero,

$$SAR_{i0} = \frac{u_{i0}}{s_E(u_i)}, \tag{26}$$

where u_{i0} is the abnormal return for security-event *i*. The estimated event-period standard deviation is

$$s_E(u_i) = \left\{ \frac{1}{11-1} \sum_{t=-5}^{5} \left(u_{it} - \bar{u}_i \right)^2 \right\}^{1/2}, \tag{27}$$

where $\bar{u}_i$ is the sample mean of u_{it} from the 11-day event period. The standardized abnormal return using the standard deviation estimated over the event period omitting day *d* is $SAR_{i0(\text{omit } d)}$, from which we compute the "pseudo-value" $\theta_{i0(\text{omit } d)} = 11 SAR_{i0} - 10 SAR_{i0(\text{omit } d)}$. The jackknife estimator is the mean of the pseudo-values,

$$\theta_{i0} = \frac{1}{11} \sum_{d=1}^{11} \theta_{i0(\text{omit } d)} \,. \tag{28}$$

The grand mean across the sample of N security-events is

$$\Theta_0 = \frac{1}{N} \sum_{i=1}^{N} \theta_{i0} \tag{29}$$

and the cross-sectional sample standard deviation is

$$s_{0(\text{Jackknife})} = \left\{ \frac{1}{N-1} \sum_{i=1}^{N} (\theta_{i0} - \Theta_0)^2 \right\}^{1/2} \,. \tag{30}$$

The jackknife statistic is

$$t_{\text{Jackknife}} = \sqrt{N} \Theta_0 / s_{0(\text{Jackknife})} \,, \tag{31}$$

and is approximately normal with mean zero and unit variance (Giaccotto and Sfiridis, 1996). For testing a multi-day window, the process is similar except that SAR_{j0} is replaced by the standardized cumulative abnormal return; for example, for an 11-day window

$$SCAR_i = \frac{\sum_{t=-5}^{+5} u_{it}}{\sqrt{11} s_E(u_i)} \tag{32}$$

The standard deviations (basic and omitting a day) still are estimated across the 11-day event window.

4. Results

4.1 Statistical properties of returns

Table 2 reports statistics of the 54 countries' equity returns represented in the sample before random selection (and before dropping the least often traded quartile of each market). Large developed markets such as Canada, Japan and the U.K. are heavily represented, but markets that individually have less than 5% of the stock return-days in the sample of stocks with returns collectively make up 53.4% of all return-days.

[Insert Table 2 here.]

The descriptive statistics of returns in Table 2 are averages of statistics calculated at the individual security level. For most markets, the average of stocks' median returns is close to zero. However, there is wide variation in the average of mean, standard deviation and percentage of returns equal to zero. Many average means appear to be distorted by outliers. The trimmed means (dropping the most extreme ½% of individual stock means in each tail) are more reasonable but still appear to be outlier-driven compared to the medians, consistent with non-normality. The average skewness and excess kurtosis of returns in the overall data set and for most markets are markedly greater than zero, suggesting that non-normal returns are pervasive. This suggests that parametric statistics may not perform well in multi-country samples.

Table 3 reports the properties of event-day abnormal returns for the 100,000 randomly selected security-events (panels A and B) and for portfolios of 100 security-events each (panels C and D) in the final sample when no abnormal performance is introduced. The results reflect the exclusion of stocks with large numbers of missing returns described in section 3.1. There are 100,000 lumped returns but due to missing price days, there are 88,333 trade-to-trade returns. The abnormal returns are positively skewed and fat-tailed. For example, the market-adjusted trade-to-trade returns have a skewness of 156.45 and excess kurtosis of 26,272.69. Several tests of normality (not reported in the table) all indicate that the abnormal returns are not normally distributed. Market model and lumped abnormal returns have similar properties. The average skewness and excess kurtosis in this data set far exceed the corresponding results in the literature for U.S. stocks. Cowan and Sergeant (1996) report that market-model abnormal returns in the most thinly traded Nasdaq sample in 1983–1993 have average skewness of 0.68 and excess kurtosis of 26.51. Campbell and Wasley (1993) report, for Nasdaq securities, average skewness and excess kurtosis for market model returns of 0.96 and 16.98 from 12/14/1973 through 12/20/1987.

[Insert Table 3 here.]

In panels C and D of Table 3, for 1,000 portfolios of 100 securities the returns are significantly less skewed with less kurtosis. The returns of portfolios with 100 securities still are not normally distributed, with skewness between 14 and 16 and excess kurtosis greater than 250.[4] In contrast, Campbell and Wasley (1993) report that for portfolios of 100 Nasdaq stocks, the raw and abnormal returns are normally distributed. We conclude that random event-study samples of non-U.S. stocks exhibit far more severe departures from normal return distributions than U.S. stocks.

Non-normal distributions at the security level do not mean that parametric tests are necessarily misspecified. However, tests such as the Patell (1976) test that make use of security-level parameters and normal distribution assumptions are most likely to be misspecified.

[4] Winsorizing the returns has been suggested, but given the degree of non-normality this is unlikely to correct the misspecification of the test statistics.

4.2 Simulations with multi-country random samples

Table 4 and Figure 1 report the simulation results for a one-day event window. Because the seeded abnormal return is known, we report one-tailed test results. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% binomial success probability, are 3.3% to 6.8%. The one-day results in panels A and B show that using trade-to-trade returns, the portfolio time-series standard deviation (CDA), generalized sign (GST), and rank test are well specified. The rejection rates under the null of the Patell, CDA, rank and jackknife tests are, at least for one tail, below the lower confidence limit for the nominal 5% significance level. From a practical standpoint, a test that does not reject the null too frequently could be considered acceptable. However, the fact that the Type I error rate is significantly less than the nominal test size raises the question whether the rate is stable across different test conditions. The jackknife test rejects the null too often for lower-tail tests. In panels C and D using lumped returns, the patterns across tests under the null do not differ greatly from panels A and B, although more rejection rates are below the lower confidence limit. An exception is the upper-tailed GST applied to market-model abnormal returns based on lumped returns (panel D), where the rejection rate of 6.9% exceeds upper 99% confidence limit of 6.8%

[Insert Table 4 and Figure 1 here.]

For the one-day event window the choice of method lies with the relative power of the test statistics. The CDA test statistic is the worst in terms of power no matter how the abnormal returns are calculated. The best candidates for a powerful test statistic are the generalized sign test when market-adjusted trade-to-trade returns, and either the generalized sign test or rank test when the market model is used to generate abnormal returns. When market-adjusted lumped returns are used, the rank test is more powerful than the generalized sign test. We conclude that for testing the one-day stock-price reaction, the nonparametric statistics dominate. The Patell test, although more powerful than the CDA test, frequently rejects the true null hypothesis too often.

Table 5 and Figure 2 report that, using the three-day event window (–1, +1), the Patell, GST and jackknife applied to cumulative abnormal returns reject the null hypothesis too often. In the case of the GST, we conjecture that the source of the misspecification is the outliers that characterize highly volatile, skewed and fat-tailed return distributions. When a noise-driven large price increase is quickly reversed, a large positive return is followed by a negative return that is smaller in absolute value, so that the sum is positive despite the value of the stock being unchanged. Thus, the imbalance between positive and negative return leads Z_G above the critical value too often. A natural modification to the GST to reduce the impact of outlier returns is to apply it to buy-and-hold abnormal returns. If our conjecture is correct, using buy-and-hold returns should eliminate this source of misspecification because the compounding process correctly represents the effect on value of a positive followed by an offsetting negative return. Table 5 shows that the generalized sign test applied to buy-and-hold returns does not reject the true null hypothesis significantly more often than the nominal 5% test size, consistent with the conjecture.

[Insert Table 5 and Figure 2 here.]

Similar to the day zero results, Table 5 reports that the CDA test is the least powerful in three-day windows, rarely detecting abnormal return when it is present. Campbell and Wasley (1993) similarly find the CDA test to be substantially less powerful than the Patell and rank tests in multi-day windows. They also find the Patell test statistic to be severely misspecified in multi-day event periods. Table 5 also shows that whether market-adjusted or market model abnormal returns are used, and whether the returns are trade-to-trade or lumped, the generalized sign test using buy-and-hold returns is well specified and is the most powerful of the test statistics, with rejection rates under the alternative hypothesis ranging from 93.8% with a –0.5% seed to 100% when the absolute value of the seed is 1% or greater.

Table 6 and Figure 3 show that for the (–5, +5) event window, the generalized sign test applied to buy-and-hold returns continues to be well specified and to dominate in terms of power. The rank test continues to have the correct size, but its power diminishes relative to shorter windows. The rank test rejects in less than a third of the samples when the seed is positive or negative 1%, whereas the generalized sign test applied to buy-and-hold returns rejects in over 99% of samples.

[Insert Table 6 and Figure 3 here.]

The results for the jackknife test in Tables 5 and 6 are mixed. Increasing the abnormal returns increases the power of the test only for the market-adjusted model, while for the market model the power of the test decreases when we seed relatively large positive or negative abnormal returns. The decreasing power at greater absolute values of abnormal returns is an artifact of the jackknife procedure for estimating standard deviation, combined with the effects of severe non-normality and thin trading on the market model parameter estimates. Appendix B provides a more detailed explanation.

We conclude that for multi-day windows, the generalized sign test with buy-and-hold abnormal trade-to-trade returns based on the market model appears to be the best choice. In addition, the use of lumped returns appears to make little difference. Hence, we conduct the remaining simulations on trade-to-trade returns only.

4.3 Simulations using random samples with a variance increase on the event date

Brown and Warner (1985) report that the variance increase on the event date adversely affects the specification of the test statistics based on variance estimates from outside the event window: using a time-series of non-event period data to estimate the variance of the mean excess return will result in too many rejections of the null hypothesis that the mean excess return is equal to zero.

We use the method of Boehmer, Musumeci and Poulsen (1991) to simulate a stock-return variance increase on day zero. For each security-event i, we generate a pseudo-random standard normal value, multiply it by the standard deviation of i's estimation period market-adjusted returns or market-model residuals s_i and add the product to the day zero return.

The results are in Table 7. Panels A and B report that the Patell test is the most powerful in the upper and lower tail, but severely misspecified (when the null hypothesis is true the rejection rates are 13.3% and 14.5% lower and upper tail, respectively). The standardized cross-sectional test is correctly specified and but less powerful than the Patell. The generalized sign test is the most powerful in the upper tail but rejects the true null hypothesis too often against a lower-tailed alternative. The rank test is powerful in the lower tail but rejects a true null too often against a lower-tailed alternative. The CDA and jackknife tests continue to be weaker than the GST and rank when well specified. Panels C through E report that for the (–1, +1) and (–5, +5) event windows, the generalized sign test using buy-and-hold returns is well specified and again the most powerful, especially for the smallest seeded abnormal returns of plus or minus half of a percent.

[Insert Table 7 here.]

Corrado and Zivney (1992) present a version of the rank test that is adjusted for variance increases by standardizing the abnormal return on the event date only. In simulations not reported in a table, we find this test to be severely misspecified in multi-country samples with a simulated variance increase. Because ranks are based on the combined estimation and event period, and standardized abnormal returns in multi-country samples are more likely to exhibit extreme values, standardizing only on the event date could distort the ranks. We therefore introduce a further variant of the rank test in which abnormal returns are standardized each day of the estimation and event periods before ranking. The results are in Table 7. The standardized rank test tends to be less powerful than the rank test rejecting a true null too often against a lower-tailed alternative. However, for three- and 11-day windows it is well specified. Nonetheless, the GST using buy-and-hold returns is well specified and is the most powerful. We suggest that in multi-country samples where a sharp event-induced variance increase is suspected, and there is a one-day event window, significant results from the generalized sign, rank or standardized rank tests be interpreted with caution.

4.4 Simulations with country-clustered samples

The small populations and limited trading history of many markets in the data set raises the potential concern that a sample from a single market or a few markets could suffer from extensive cross-correlation, which the literature shows can cause various tests to become misspecified. Therefore, we repeat the main simulations using country-clustered samples. That is, each of the 1,000 samples contains 100 security-events that are from a single market, but the markets vary across the 1,000 samples. To create the samples, we use the initial set of 250,000 security-events described in section 3.3, but this time we sort the data set by market, and by order of random drawing within each market, before forming samples. We use a number of samples from each market that is proportional to the number of stock return-days (the sum of the number of available days for each stock) from each market in the data set.

The results are in Table 8. For day zero, the generalized sign, CDA and rank tests are well specified. However, the GST and rank statistics dominate the CDA in terms of power. These conclusions hold whether market-adjusted or market model abnormal returns are used. For day zero and multi-day windows, the Patell test is consistently misspecified and less powerful than the rank and generalized sign tests. With the market model, the rank statistic is the most powerful well-specified test for day zero. With a longer event window the most powerful well-specified test is the generalized sign test using BHARs. It does not appear that tests on single-country samples suffer significant distortion from increased cross-correlation. A caveat is that our method forces the number of samples to be proportional to the markets' representation in the data set of daily stock returns from which we draw, resulting in more samples from larger markets with longer histories.

[Insert Table 8 here.]

4.5 Simulations with samples from the most concentrated markets

The results so far indicate that two nonparametric tests, the generalized sign and rank tests, perform well in non-U.S., multi-country and single-country samples. Some markets in the data set are long established as relatively large, developed, integrated markets in countries with equity-oriented financial systems. Others are only getting started in the latter years of our sample period, and still others are at various stages of development in various years that we study. In this section, we investigate whether the main results hold up in samples restricted to less advanced markets. To gauge a market's degree of development, we use the extent to which trading is concentrated in a few issues.[5] To measure trading concentration while allowing for changing market characteristics over time, we divide the data into an initial four year period and five subsequent three year periods. We calculate each stock's daily market value traded by multiplying its volume by the closing price the same day. Our empirical proxy for a market's concentration is a Herfindahl index calculated using the median daily market value traded in the four- or three-year period.[6]

We restrict the simulation samples each period to the ten markets with the largest concentration proxy in the period, excluding any market with fewer than 20 issues with data in the period. We examine only the generalized sign and rank test, and for multi-day windows we apply the generalized sign test only to BHARs. The results are in Table 9. Both tests exhibit proper specification and power similar to the main simulations. We conclude that the superior performance of the two nonparametric tests is robust to trading concentration.

[Insert Table 9 here.]

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[5] Trading concentration is important because of the potential effects on other stocks of dominant issues' trading. For example, Braun and Larrain (2008) report that large IPOs can alter the return distributions of other stocks in emerging markets.

[6] The largest developed markets rarely appear among the ten most concentrated markets. France and Australia appear on the top ten list in the first subperiod, Germany in the second, Italy in the first two and Canada in the fourth. Neither Japan nor the U.K. is ever among the ten most concentrated markets.

4.6 Samples from the most non-normal markets and with market-moving events

One could argue that although we exclude U.S. stocks, the simulation samples continue to be dominated by large developed markets, where returns depart less dramatically from normality than in other markets. Table 10 reports simulations on the markets with the most non-normally distributed equity returns in each three- to four-year period. The generalized sign and rank tests continue to perform well, although the upper-tail rejection rates of the rank test sometimes exceed the upper confidence limit and the generalized sign test tends to be more powerful.

[Insert Table 10 here.]

In concentrated markets, some stocks could be a large enough component of local market indexes that events affecting the stocks also affect the market indexes, making it difficult to detect abnormal performance by adjusting the stock return using the local market index. To investigate this possibility, we multiply the each stock's seeded return by the stock's fraction of the market's capitalization, and add the product to the market index before calculating abnormal returns. The results in Table 11 show that the generalized sign and rank tests continue to be well specified and powerful in single-day tests. In multi-day windows, the use of the market model is helpful for the specification and power of the rank test, but the generalized sign test is more powerful overall and is well specified.[7]

[Insert Table 11 here.]

[7] Stocks trading in concentrated markets could be more correlated with world stock returns than local returns due to limited local information production. To address this possibility, in a robustness check not reported in a table, we calculate abnormal returns using an expanded market model with both local and U.S. level one market indexes from Datastream. Following Jin and Myers (2006) we introduce two leads and lags for the local and U.S. indexes. The specification and power of the rank and generalized sign tests using the expanded model do not differ significantly from the single-factor, local-index market model

5. Multi-country event study of merger and acquisition announcements

The simulation evidence provides some reassurance that the market-adjusted and market-model methods with local indexes, in conjunction with the nonparametric rank and generalized sign tests, properly applied, provide reliable results in multi-country samples. In this section, we conduct a multi-country event study on a real sample to see whether plausible results are obtained using the methods that perform well in simulation. We examine merger and acquisition announcements, which have received extensive study in U.S. and other single country and single region samples. Jensen and Ruback (1983) summarize several studies that report two-day announcement period abnormal returns to U.S. acquiring firms that are insignificant and abnormal returns to targets that are significantly positive, ranging from about 8% to 35% depending on the form and ultimate outcome of the transaction. Andrade, Mitchell and Stafford (2001) similarly report three-day announcement period abnormal returns that are insignificant for U.S. acquirers and average a significantly positive 16% for targets over 1973–1998. Campa and Hernando (2004) report smaller (about 4%), but still significantly positive, target abnormal returns and insignificant acquirer returns in a multi-country European Union sample from 1998-2000.

From the deals database of Thomson One Banker, we obtain all merger and acquisition announcements in 1988–2006. There are 31,615 announcements, some of which we eliminate because the target and acquirer CUSIP are identical or because the Datastream DSCD code for the target or acquirer or the announcement date is unavailable from the deals database. We further eliminate all but the first announcement for each target, announcements in which the target or acquirer is a financial or utility firm (SIC code beginning with four or six) and those where the acquirer is a U.S. firm. We include only cross-border transactions in which more than 49% of target outstanding shares are to be purchased. These criteria produce a sample of 282 announcements. We find sufficient Datastream data for 222 targets and 263 acquirers to estimate abnormal returns in the 11-day event period.

The results are in Table 12. Consistent with Jensen and Ruback (1983), Andrade, Mitchell and Stafford (2001) and Campa and Hernando (2004), we find significant positive results for targets regardless of the event window or the use of market-adjusted or market model returns. For example, using the market model, Table 12, Panel B reports a three-day announcement-period target CAR of 10.23%, significant at 1% using the rank test, and a mean three-day BHAR of 10.17%, significant using the generalized sign test.

[Insert Table 12 here.]

Also comparable to the literature, acquiring firms have insignificant returns on average. For example, using the market model, Table 12, Panel D reports a mean acquirer three-day CAR of –0.29%, which does not differ significantly from zero at conventional levels using the rank test. Likewise, the mean three-day acquirer BHAR of –0.48% is insignificant using the generalized sign test.

To the extent that it is reasonable for target and acquiring firm stock returns to follow similar patterns around world, these findings provide further comfort for researchers conducting multi-country event studies. Relatively simple methods, without international market indexes, appear to be sufficient to allow the researcher to isolate stock-price reactions from noise.

6. Conclusions

We examine the performance of event-study statistical tests applied to market-adjusted and market-model adjusted abnormal trade-to-trade and lumped returns in simulations using actual return data on 48,258 ordinary share issues from 54 non-U.S. markets over 1986–2006. In random samples, security abnormal returns, and even portfolio abnormal returns for 100-stock samples, depart widely from a normal distribution. The simulation results show that two common parametric tests are weak and frequently misspecified. Two nonparametric tests, the generalized sign and rank tests, are well specified and powerful under most test conditions simulated. A qualification to this conclusion is that in the case of the generalized sign test applied to multi-day windows, buy-and-hold abnormal returns rather than cumulative average abnormal returns must be used for correct test specification. With this provision, the generalized sign test tends to be more powerful than the rank test in multi-day windows.

The performance of the rank and especially generalized sign tests holds up when we consider country-clustered samples, samples from the most concentrated or markets with the most non-normal equity return distributions in each period, and samples with market-moving events. In the case of a substantial variance increase on the event date, significant results from the tests should be interpreted with caution.

Apart from the selection of a test statistic, simple market-adjusted and market-model methods of calculating abnormal returns with local market indexes, without converting to a common currency, appear to be sufficient. The lumped return method, in which a zero return is recorded for a day on which no price is available due to non-trading, appears to offer no advantage over the more standard trade-to-trade method.

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Appendix A. Sample selection details

This appendix provides more details of the data selection procedure in section 3.1. We exclude a security if the name record on Datastream includes one of the following codes that indicates it is not an ordinary share issue: CV, CONV, CVT, FD, OPCVM, PREF, PF, PFD, PFC, PFCL, RIGHTS, RTS, UNIT, UNITS, WTS, WT, WARR, WARRANT, and WARRANTS.

To avoid using securities traded in the U.S., we exclude a security if any of the following applies: a mnemonic (a Datastream security code) beginning with U: or @, or an exchange code of NYS, ASE, NAS, XBQ, BOS, CHI, MID, NMS, OTC, PBT, PHL, PSE or XNT. The mnemonic is usually in the format market code:ticker, with market code: omitted for U.K. stocks. As tickers are recycled within markets, mnemonics do not uniquely identify stocks within Datastream.

Datastream includes a field for each equity issue that identifies the "associated" level one market index. At the time we downloaded much of the data, late 2004 and early 2005, the field for dead stocks was essentially always filled with TOTMKUK, the code for the United Kingdom level one index, regardless of the market on which the stock traded while alive. This appears to be largely corrected in new downloads starting in 2007. To ensure that we use the correct index for dead stocks, we identify dead stocks by searching the name field for the codes DEAD, SUSP, DELIST, EXPD, DEL, DELEST, DELISTED, and DEF. We use the market code portion of the mnemonic to identify the stock's market and select the corresponding market index.

One of the frustrations of dealing with Datastream is that the market code portion of the security mnemonic, the exchange code and the market portion of the level one Datastream Global index mnemonic are different. To select level one market indexes for dead stocks, we use the following pairings of security-mnemonic market code (level one market index mnemonic):

A	TOTMKAU	KO	TOTMKKO
AG	TOTMKAR	L	TOTMKMY
B	TOTMKBG	LX	TOTMKLX
BN	TOTMKBN	M	TOTMKFN
BR	TOTMKBR	MC	TOTMKMC
C	TOTMKCN	MX	TOTMKMX
CB	TOTMKCB	N	TOTMKN
CL	TOTMKCL	O	TOTMKOE
CN	TOTMKCH	P	TOTMKPT
CP	TOTMKCP	PE	TOTMKPE
CZ	TOTMKCZ	PH	TOTMKPH
D	TOTMKBD	PK	TOTMKPK
E	TOTMKES	PO	TOTMKPO
ED	TOTMKED	Q	TOTMKTH
EG	TOTMKEY	R	TOTMKSA
F	TOTMKFR	RS	TOTMKRS
G	TOTMKGR	S	TOTMKS
GD	TOTMKPH	SL	TOTMKCY
H	TOTMKNL	T	TOTMKSG
ID	TOTMKID	TK	TOTMKTK
I	TOTMKIT	TW	TOTMKTA
IN	TOTMKIN	U	TOTMKUS
IS	TOTMKIS	V	TOTMKVE
J	TOTMKJP	W	TOTMKSD
K	TOTMKHK	Z	TOTMKNZ
KN	TOTMKKN	ZI	TOTMKZI

If the associated index field is empty and the stock is not dead, or if the stock is dead and we cannot identify a level one market index corresponding to its market, we drop the stock from the data set.

Another problem in our experience with Datastream has to do with the trading volume date we use as part of our market-concentration measure. A small amount of volume data is misreported in the data set we downloaded for our simulations. Specifically, 61 of the originally downloaded volume figures are negative. As of mid-2008, Datastream appears to have changed the negative volumes to zero or missing. Our spot checking uncovers no changes to volume figures that were not negative in our original download.

Appendix B. Explanation of jackknife power behavior

When the sample returns are positively skewed and fat tailed, and many securities are thinly traded, market model parameter estimates can be quite small in absolute value. As a result, when there is no seeded abnormal performance, the measured abnormal returns tend to be relatively small and steady across the event period. Consistent with this and as reported in Table 3 the mean portfolio abnormal returns using the market model are 0.001 for both trade-to-trade and lumped returns whereas the mean for market-adjusted returns are 0.004 and 0.003, respectively. When a non-zero seeded abnormal return is introduced, it drives the event-period standard deviation of market-model abnormal return upwards, except the jackknife standard deviation when day zero is deleted, and therefore drives down the absolute value of each $SAR_{i0(\text{omit } d)}$ except $SAR_{i0(\text{omit } 0)}$. The greater the distortion of the jackknife standard deviation, the greater is the difference between SAR_{i0} and $SAR_{i0(\text{omit } d,\, d\neq 0)}$ potentially making the sign of $\theta_{i0(\text{omit } 0)} = 11SAR_{i0} - 10SAR_{i0(\text{omit } 0)}$ opposite to that of the seeded abnormal return.[8] Consequently θ_{i0}, being the average of 10 (11–1) small pseudo values $\theta_{i0(\text{omit } d,\, d\neq 0)}$ and one large sign-reversed value $\theta_{i0(\text{omit } 0)}$, is potentially sign-reversed also.

To illustrate, Table A–1 reports, for an arbitrarily selected security-event, the values of $SAR_{i0(\text{omit } d)}$ and the cumulative adjustment of the jackknife estimate θ_{i0} as successive days are omitted and the resulting $\theta_{i0(\text{omit } d)}$ incorporated into θ_{i0}. While for market-

[8] The sign change occurs if $\left|SAR_{i0(\text{omit } 0)}\right| > \left|\left(1+\frac{1}{11-1}\right)SAR_{i0}\right|$.

adjusted returns the effect of $\theta_{i0(\text{omit }0)}$ on θ_{i0} is counterbalanced approaching day +5, the effect is persistent for the market model-adjusted returns.

The market model parameters' for the security-event are, not surprisingly, small, leading to steady and low excess returns around the event; thus the event induced increase in the standard deviation is greater and the sign reversal is persistent, leading to a sign reversal of θ_{i0}, contributing to reducing the power of the test for the full sample.

Table B-1
Event induced standard deviation shift and the behavior of the jackknife statistic

For an arbitrarily selected security-event, the values of $SAR_{i0(\text{omit }d)}$ and the cumulative adjustment of $\sum_{d=-5}^{d\text{ last}} \theta_{i0(\text{omit }d)}$ to the accrual of each $\theta_{i0(\text{omit }d)}$ from day –5 to day +5. The estimated market model parameters are intercept = 0.003080928, beta = -0.009818194.

	Market model				Market-adjusted			
	Seeded abnormal return				Seeded abnormal return			
	–5%		+5%		–5%		+5%	
d_{last}	$SAR_{i0(\text{omit }d)}$	$\sum_{d=-5}^{d\text{ last}} \theta_{i0(\text{omit }d)}$	$SAR_{i0(\text{omit }d)}$	$\sum_{d=-5}^{d\text{ last}} \theta_{i0(\text{omit }d)}$	$SAR_{i0(\text{omit }d)}$	$\sum_{d=-5}^{d\text{ last}} \theta_{i0(\text{omit }d)}$	$SAR_{i0(\text{omit }d)}$	$\sum_{d=-5}^{d\text{ last}} \theta_{i0(\text{omit }d)}$
-5	-3.357	-5.151	2.967	4.568	-2.903	-4.428	2.897	3.124
-4	-3.356	-10.312	2.968	9.128	-2.916	-8.733	2.770	7.522
-3	-3.356	-15.473	2.968	13.687	-2.924	-12.959	2.769	11.932
-2	-3.357	-20.627	2.968	18.253	-2.889	-17.531	2.845	15.582
-1	-3.356	-25.792	2.969	22.808	-2.993	-21.060	2.780	19.883
0	**-697.2**	**6907.5**	**616.69**	**-6109.8**	**-6.674**	**12.220**	**6.226**	**-10.279**
1	-3.357	6902.3	2.968	-6105.3	-2.890	70.657	2.791	-6.093
2	-3.356	6897.2	2.968	-6100.7	-2.941	3.609	2.768	-1.682
3	-3.356	6892	2.968	-6096.1	-2.928	0.575	2.768	2.732
4	-3.358	6886.8	2.967	-6091.6	-2.928	-4.760	2.961	5.214
5	-3.356	6881.7	2.968	-6087.1	-2.976	-8.466	2.775	9.565
θ_{j0}		**625.6**		**-553.4**		**-0.770**		**0.870**

Table 1

Articles using event-study methods with multi-country samples

Examples of articles that report event-study results for samples from more than one country. SUR is seemingly unrelated regressions, also called joint generalized least squares; MM: market model abnormal returns; MAR; market-adjusted returns; L: local market index or local currency; G: global market index; R; regional (multi-country) market index; C: converted to express returns in a single currency; CDA: crude dependence adjustment, i.e. the portfolio time-series standard deviation based t-test of Brown and Warner (1980, 1985); GST: generalized sign test where the null hypothesis is that percent positive in event window and estimation period are equal; "t": article indicates t-test without further distinction; NA: not applicable; NR: not reported. Journals: AE: Applied Economics; EMR: Emerging Markets Review; EFM: European Financial Management; JAE: Journal of Accounting and Economics; JBF: Journal of Banking and Finance; JBFA: Journal of Business Finance and Accounting; JFE: Journal of Financial Economics; JFM: Journal of Financial Markets; JFQA: Journal of Financial and Quantitative Analysis; JIE: Journal of International Economics; JLE: Journal of Law and Economics; RFS: Review of Financial Studies.

Article	N	Countries	Model	Index	Curr.	Windows	Tests	Estimation period
Akhigbe, Frye and Whyte (2005), JBFA	532	8	SUR	L	L	(-1, +1)	SUR	NA
Bailey, Karolyi and Salva (2006), JFE	2,530	40	MM	L	L	(-1, +1)	CDA	(-200, -11)
Bhattacharya, Galpin and Haslem (2007), JLE	3,076	NR	MM	L	L	(-1, +1), (-1, +3)	"t"	(-270, -30)
Chakrabarti, Huang, Jayaraman and Lee (2005), JBF	455	46	MAR	L	L	(0), (0, +1), (-10, -1), (+2, 10)	"t"	NR
DeFond, Hung and Trezevant (2007), JAE	53,197	26	MM, MAR	L	L	(0, +1)	NR	(-120, -21)
Doidge (2004), JFE	37	11	MM	L	L	(-1, +1), (-5, +1), (-5, +5)	Patell	(-244, -6)
Ekkayokkaya, Holmes and Paudyal (2007), EFM	963	15	MAR	L	L	(-1, +1)	"t"	NA
Faccio, McConnell and Stolin (2006), JFQA	4,429	17	MAR	L	L	(-2. +2)	"t"	NA
Forbes (2004), JIE	21,651	46	MM	G	L	Two weeks, 12 weeks	None used	One year
Harvey, Lins and Roper (2004), JFE	1,348	18	MM	L	L	(-1, +4)	Patell, GST	(-120, -20)
Jegadeesh and Kim (2006), JFM	191,174	7	MAR	L	L	(0), (0, +1), (0, +2), (0, +22 …)	CDA	NR
Keloharju, Knüpfer and Torstila (2006), RFS	360	24	MAR	L	L	(0), (+1), (-1, +1), (-5, +5) …	CDA, signed rk	NR
Korczak and Bohl (2005), EMR	56	6	MM	L	L	(-5, -1), (-1, +1), (+1, +5) …	"t", signed rk	various
Norden and Weber (2004), JBF	397	NR	MM, MAR	R	L	(-30, -2), (-1, +1), (+2, +30) …	CDA, sign, signed rk	(-90, +90)
Scholtens and Peenstra (2008), AE	1,247	5	MM	L	L	(+1)	CDA, Corrado rank	250 days pre
Zhang (2002), JAE	8,135	22	MM	L	C	(0, +2)	CDA, bootstrap	100 days pre

Table 2
Descriptive statistics of daily trade-to-trade returns individual equities for 54 countries, 1988-2006

The sample includes stocks (ordinary shares) that have Datastream price data available starting before 2004 and ending no earlier than 1988. The inclusion criteria are based on the trading history in the Datastream database, not necessarily a stock's entire history as a public issue. We calculate returns using Datastream split-adjusted prices and dividends. The ½% trimmed mean column reports the trimmed mean (a robust estimator of location) across stocks, of the untrimmed mean daily return, where the trimming removes the ½% most extreme observations in each tail of the sample.

				Mean across stocks of:						
Country	Number of stocks	Mean no. of returns per stock	% of the overall sample	Mean	Mean (½% trimmed)	Median	Standard deviation	Skewness	Excess kurtosis	Percent of zero returns
Overall	48,258	1665	100.00%	0.077	0.008	0.001	2.696	4.891	229.823	20.7%
Argentina	135	1350	0.20%	0.171	0.081	0.000	2.847	3.015	88.436	14.2%
Australia	2263	1369	3.90%	0.005	0.003	0.000	0.109	2.773	128.021	18.2%
Austria	228	1646	0.50%	0.002	0.003	-0.001	0.073	5.961	164.610	19.1%
Belgium	886	1130	1.20%	0.184	0.024	-0.001	4.866	7.033	220.496	12.1%
Brazil	798	820	0.80%	0.122	0.027	0.003	1.821	3.744	111.260	11.5%
Canada	6786	1644	13.90%	0.016	0.011	0.000	0.319	5.614	206.772	24.8%
Chile	259	1362	0.40%	0.007	0.007	0.001	0.064	2.091	58.124	13.2%
China	1435	1894	3.40%	0.000	0.000	0.000	0.029	0.230	18.577	5.0%
Colombia	156	375	0.10%	0.052	0.021	-0.004	0.401	2.009	51.534	3.9%
Cyprus	140	1124	0.20%	0.003	0.003	0.000	0.098	5.856	142.557	19.9%
Czech Rep.	32	2061	0.10%	0.000	0.000	0.000	0.026	0.397	11.363	32.0%
Denmark	379	1567	0.70%	0.046	0.006	0.000	1.201	2.081	116.856	12.0%
Ecuador	3	4	0.00%	-0.008	-0.008	-0.001	0.053	-2.914	9.073	0.1%
Finland	266	1787	0.60%	0.001	0.001	0.000	0.041	1.778	58.237	22.2%
France	2094	1542	4.00%	0.012	0.004	0.001	0.356	3.616	152.092	13.4%
Germany	6306	1016	8.00%	0.023	0.003	0.009	0.295	3.780	170.197	26.8%
Greece	472	2092	1.20%	0.015	0.014	0.000	0.371	22.056	764.598	11.9%
Hong Kong	1150	1875	2.70%	0.004	0.002	0.000	0.149	4.491	216.371	14.9%
Hungary	47	1549	0.10%	0.006	0.004	0.000	0.102	1.980	49.765	9.9%
India	1315	1966	3.20%	0.004	0.003	0.000	0.079	1.813	67.243	7.7%
Indonesia	415	1394	0.70%	0.004	0.003	0.000	0.081	3.144	79.857	20.6%
International	89	1308	0.10%	0.001	0.001	0.000	0.103	4.209	507.578	3.2%
Ireland	138	2268	0.40%	0.002	0.001	0.000	0.055	2.883	255.134	52.7%
Israel	762	1485	1.40%	0.010	0.002	0.000	0.076	2.531	96.376	16.6%
Italy	565	2436	1.70%	0.464	0.192	0.000	17.352	20.866	731.872	15.1%

Table 2 continued

Country	Number of stocks	Mean no. of returns per stock	% of the overall sample	Mean across stocks of: Mean	Mean (½% trimmed)	Median	Standard deviation	Skewness	Kurtosis	Percent of zero returns
Japan	3715	2663	12.30%	0.382	0.025	0.000	19.914	8.989	511.614	12.4%
Luxembourg	113	1046	0.00%	0.003	0.003	0.000	0.066	6.001	179.580	16.1%
Malaysia	1004	2294	0.03%	0.001	0.001	0.000	0.043	2.169	47.749	20.0%
Mexico	327	982	0.00%	0.013	0.007	0.001	0.129	2.100	93.828	9.3%
Morocco	12	513	0.00%	0.002	0.002	0.000	0.036	11.781	280.527	70.2%
Netherlands	591	1863	0.01%	0.034	0.014	0.000	1.020	5.069	492.191	28.5%
New Zealand	339	1430	0.01%	0.011	0.003	0.008	0.093	3.981	221.934	27.1%
Norway	430	1194	0.01%	0.192	0.058	0.000	2.340	1.993	54.138	13.2%
Pakistan	293	1264	0.01%	0.008	0.006	0.001	0.090	3.928	114.510	7.0%
Peru	193	634	0.00%	0.010	0.009	0.003	0.125	2.091	47.971	7.7%
Philippines	296	1565	0.01%	0.047	0.006	-0.001	0.776	5.190	189.201	20.8%
Poland	278	1371	0.01%	0.001	0.001	0.000	0.041	1.098	41.389	11.8%
Portugal	222	1183	0.00%	0.030	0.014	0.002	0.698	11.563	331.729	12.8%
Romania	47	1571	0.00%	0.075	0.066	0.000	3.016	11.666	608.271	15.8%
Russian Fed.	117	342	0.00%	0.437	0.223	0.002	9.467	3.019	66.736	8.0%
Singapore	853	1743	1.90%	0.020	0.001	0.016	0.064	1.813	40.001	19.7%
Slovakia	1	47	0.00%	0.000	0.000	0.000	0.000	—	—	1.2%
South Africa	865	1345	1.40%	0.008	0.007	0.000	0.165	3.459	138.087	20.0%
Spain	261	2334	0.80%	0.033	0.014	0.000	1.313	14.828	540.357	16.3%
Sri Lanka	272	1317	0.40%	0.007	0.007	0.000	0.124	4.396	137.067	14.3%
Sweden	942	1306	1.50%	0.081	0.007	0.000	1.432	2.927	86.111	16.1%
Switzerland	679	1573	1.30%	0.179	0.052	0.000	5.326	7.614	430.834	14.7%
Taiwan	1274	1969	3.10%	0.000	0.000	0.000	0.032	1.011	33.400	9.0%
Thailand	885	1440	1.60%	0.003	0.003	-0.001	0.169	2.932	144.274	11.1%
Turkey	371	2561	1.20%	0.004	0.003	0.000	0.116	1.217	168.673	19.4%
UK	5398	1847	12.40%	0.141	0.009	0.000	3.678	6.907	461.158	44.4%
Venezuela	64	960	0.10%	0.017	0.009	0.006	0.081	2.254	80.448	13.6%
Zimbabwe	2	444	0.00%	0.029	0.029	0.000	0.401	5.029	139.258	28.1%

Table 3
Properties of day zero abnormal returns with no abnormal performance induced

The combined simulated event-study samples contain 100,000 trading days for ordinary non-U.S. stocks from 1988-2006; price and dividend data come from Datastream. Each daily stock return is calculated from the previous trading day having a non-missing price to the current trading day, including dividends. No return is calculated on a day with a missing price. Trade-to-trade returns consist of calculated returns from non-missing price days. For a stock with a missing price, the corresponding market return is added to the market return on the next non-missing price day for trade-to-trade abnormal return calculation. Lumped returns consist of trade-to-trade returns on non-missing price days and zero on missing price days. The market index for market-adjusted and market model abnormal returns is the country-specific Datastream Global Index (level one). Market-adjusted return is the stock return minus the market index return. The market model is estimated by ordinary least squares.

Abnormal return type	N	Median	Mean	Standard deviation	Skewness	Excess kurtosis
Panel A: Trade-to-trade returns – individual securities						
Market-adjusted returns	88,333	–0.001	0.004	0.448	156.450	26,272.69
Market model adjusted	88,333	–0.001	0.000	0.463	137.285	23,028.61
Panel B: Lumped returns – individual securities						
Market-adjusted returns	100,000	–0.001	0.003	0.424	165.188	29,301.84
Market model adjusted	100,000	–0.001	0.000	0.455	148.141	24,564.43
Panel C: Trade-to-trade returns – 100-stock portfolios						
Market-adjusted returns	1,000	0.000	0.004	0.047	16.340	284.382
Market model adjusted	1,000	-0.002	0.000	0.049	14.304	248.995
Panel D: Lumped returns – 100-stock portfolios						
Market-adjusted returns	1,000	0.001	0.003	0.042	16.480	290.346
Market model adjusted	1,000	-0.002	0.000	0.048	15.483	266.038

Table 4
Day zero rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006

The stocks are ordinary share issues; data come from Datastream. We randomly sample from the available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. When no trade price is reported, the stock's trade-to-trade abnormal return is set to missing and, for abnormal return calculation, the market return is added to the market return on the next non-missing price day. A lumped return is identical to the trade-to-trade return when there is no missing price on the current or previous trading day; when there is a missing price, the lumped return is zero and the market return is not adjusted. To simulate a stock-price reaction, we add a seeded return to the stock return on the selected event date (day zero). The market index is the country-specific "Total Market" index of the Datastream Global series, also called a Level 1 index; the indexes are value weighted. Market-adjusted return is the stock return minus the market return. The market model is estimated by OLS; market-model abnormal returns are prediction errors. The estimation period, for signs, standard deviations and market model parameters, is trading days –256 through –6 relative to the event; ranks for the rank test incorporate days –256 through +6. The null hypothesis of the Patell, time-series portfolio standard deviation (CDA) and jackknife tests is that the mean abnormal return on day 0 is zero. The null hypothesis of the generalized sign test (GST) is that the fraction of day 0 abnormal returns having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign. The null hypothesis of the rank test is that the mean rank of day zero is equal to that of the estimation period. Alternative hypotheses are one tailed. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% success probability, are 3.3% to 6.8%

Panel A: Market-adjusted abnormal returns based on trade-to-trade returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.996	0.995	0.972	0.643	0.053	0.073	0.618	0.986	1.000	1.000
CDA	0.711	0.615	0.275	0.093	0.013	0.037	0.120	0.292	0.631	0.713
GST	1.000	1.000	0.997	0.800	0.046	0.041	0.821	0.998	1.000	1.000
Rank	1.000	1.000	0.959	0.675	0.035	0.026	0.620	0.957	1.000	1.000
Jackknife	0.976	0.977	0.946	0.752	0.080	0.019	0.583	0.935	0.970	0.971

Panel B: Market-model abnormal returns based on trade-to-trade returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.997	0.996	0.987	0.749	0.067	0.074	0.696	0.992	1.000	1.000
CDA	0.720	0.625	0.311	0.111	0.016	0.034	0.103	0.268	0.620	0.702
GST	1.000	1.000	0.999	0.891	0.057	0.050	0.966	1.000	1.000	1.000
Rank	1.000	1.000	0.991	0.844	0.034	0.027	0.824	0.987	1.000	1.000
Jackknife	0.110	0.190	0.325	0.349	0.112	0.007	0.200	0.271	0.187	0.114

Panel C: Market-adjusted abnormal returns based on lumped returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.996	0.995	0.983	0.679	0.054	0.073	0.665	0.988	1.000	1.000
CDA	0.698	0.594	0.285	0.096	0.011	0.034	0.118	0.295	0.616	0.702
GST	1.000	1.000	0.898	0.377	0.010	0.006	0.463	0.975	1.000	1.000
Rank	1.000	1.000	0.963	0.675	0.041	0.028	0.619	0.957	1.000	1.000
Jackknife	0.985	0.987	0.971	0.849	0.083	0.016	0.699	0.968	0.985	0.983

Table 4 continued

Panel D: Market-model abnormal returns based on lumped returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.997	0.996	0.987	0.752	0.065	0.074	0.697	0.992	1.000	1.000
CDA	0.704	0.610	0.309	0.123	0.022	0.032	0.112	0.266	0.602	0.694
GST	1.000	1.000	0.998	0.853	0.041	0.069	0.976	1.000	1.000	1.000
Rank	1.000	1.000	0.992	0.839	0.034	0.026	0.820	0.986	1.000	1.000
Jackknife	0.098	0.180	0.318	0.353	0.113	0.007	0.221	0.281	0.184	0.109

Table 5

Three-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006

The stocks are ordinary share issues; data come from Datastream. We randomly sample from the available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. When no trade price is reported, the stock's trade-to-trade abnormal return is set to missing and, for abnormal return calculation, the market return is added to the market return on the next non-missing price day. A lumped return is identical to the trade-to-trade return when there is no missing price on the current or previous trading day; when there is a missing price, the lumped return is zero and the market return is not adjusted. To simulate a stock-price reaction, we add a seeded return to the stock return on the selected event date (day zero). The market index is the country-specific "Total Market" index of the Datastream Global series, also called a Level 1 index; the indexes are value weighted. Market-adjusted return is the stock return minus the market return. The market model is estimated by OLS; market-model abnormal returns are prediction errors. The abnormal returns of trading days (–1,+1) are added to create the three-day window cumulative abnormal return (CAR). The estimation period, for signs, standard deviations and market model parameters, is trading days –256 through –6 relative to the event; ranks for the rank test incorporate days –256 through +6. The null hypothesis of the Patell, time-series portfolio standard deviation (CDA) and jackknife tests is that the mean CAR is zero. The null hypothesis of the generalized sign test reported as GST is that the fraction of CARs having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign; when reported as GST(BH), the null is that the mean abnormal compounded (buy-and-hold) window return is zero. The null hypothesis of the rank test is that the mean rank in the event window is equal to that of the estimation period. Alternative hypotheses are one tailed. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% success probability, are 3.3% to 6.8%

Panel A: Market-adjusted abnormal returns based on trade-to-trade returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.995	0.994	0.722	0.285	0.042	0.073	0.333	0.776	1.000	1.000
CDA	0.585	0.459	0.064	0.013	0.003	0.035	0.066	0.146	0.527	0.617
GST	1.000	1.000	0.906	0.592	0.119	0.109	0.565	0.922	1.000	1.000
GST(BH)	1.000	1.000	0.993	0.767	0.047	0.045	0.807	0.998	1.000	1.000
Rank	1.000	0.996	0.709	0.322	0.034	0.023	0.271	0.678	0.997	1.000
Jackknife	0.959	0.956	0.817	0.496	0.117	0.015	0.219	0.650	0.947	0.954

Panel B: Market-model abnormal returns based on trade-to-trade returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.996	0.995	0.837	0.405	0.054	0.064	0.370	0.803	1.000	1.000
CDA	0.609	0.518	0.101	0.031	0.004	0.025	0.052	0.104	0.493	0.605
GST	1.000	0.992	0.715	0.492	0.218	0.227	0.510	0.755	0.999	1.000
GST(BH)	1.000	1.000	0.995	0.867	0.046	0.035	0.955	1.000	1.000	1.000
Rank	1.000	0.998	0.799	0.503	0.032	0.020	0.451	0.763	0.996	1.000
Jackknife	0.977	0.976	0.888	0.580	0.138	0.018	0.273	0.738	0.963	0.970

Table 5 continued

Panel C: Market-adjusted abnormal returns based on lumped returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.995	0.994	0.757	0.319	0.041	0.074	0.362	0.811	1.000	1.000
CDA	0.584	0.468	0.083	0.021	0.001	0.035	0.067	0.166	0.524	0.608
GST	1.000	1.000	0.985	0.841	0.326	0.252	0.789	0.987	1.000	1.000
GST(BH)	1.000	1.000	1.000	0.901	0.049	0.048	0.918	1.000	1.000	1.000
Rank	1.000	0.998	0.715	0.320	0.033	0.023	0.286	0.682	0.996	1.000
Jackknife	0.113	0.201	0.318	0.306	0.115	0.005	0.051	0.139	0.177	0.114

Panel D: Market-model abnormal returns based on lumped returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.996	0.995	0.835	0.406	0.050	0.052	0.331	0.769	1.000	1.000
CDA	0.589	0.491	0.122	0.050	0.007	0.026	0.046	0.093	0.454	0.564
GST	1.000	0.995	0.774	0.576	0.289	0.267	0.575	0.804	0.998	1.000
GST(BH)	1.000	1.000	1.000	0.938	0.049	0.032	0.981	1.000	1.000	1.000
Rank	1.000	0.997	0.797	0.509	0.031	0.019	0.445	0.766	0.996	1.000
Jackknife	0.102	0.197	0.322	0.316	0.141	0.002	0.052	0.146	0.175	0.097

Table 6

Eleven-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006

The stocks are ordinary share issues; data come from Datastream. We randomly sample from the available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. When no trade price is reported, the stock's trade-to-trade abnormal return is set to missing and, for abnormal return calculation, the market return is added to the market return on the next non-missing price day. A lumped return is identical to the trade-to-trade return when there is no missing price on the current or previous trading day; when there is a missing price, the lumped return is zero and the market return is not adjusted. To simulate a stock-price reaction, we add a seeded return to the stock return on the selected event date (day zero). The market index is the country-specific "Total Market" index of the Datastream Global series, also called a Level 1 index; the indexes are value weighted. Market-adjusted return is the stock return minus the market return. The market model is estimated by OLS; market-model abnormal returns are prediction errors. The abnormal returns of trading days –5 through +5 are added to create the 11-day window cumulative abnormal return (CAR). The estimation period, for signs, standard deviations and market model parameters, is trading days –256 through –6 relative to the event; ranks for the rank test incorporate days –256 through +6. The null hypothesis of the Patell, time-series portfolio standard deviation (CDA) and jackknife tests is that the mean CAR is zero. The null hypothesis of the generalized sign test reported as GST is that the fraction of CARs having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign; when reported as GST(BH), the null is that the mean abnormal compounded (buy-and-hold) window return is zero. The null hypothesis of the rank test is that the mean rank in the event window is equal to that of the estimation period. Alternative hypotheses are one tailed. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% success probability, are 3.3% to 6.8%

Panel A: Market-adjusted abnormal returns based on trade-to-trade returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.984	0.934	0.244	0.089	0.027	0.104	0.230	0.447	0.988	1.000
CDA	0.344	0.109	0.006	0.003	0.000	0.057	0.081	0.113	0.340	0.536
GST	1.000	0.986	0.536	0.331	0.149	0.177	0.377	0.626	0.995	1.000
GST(BH)	1.000	1.000	0.991	0.766	0.048	0.056	0.818	0.998	1.000	1.000
Rank	0.851	0.732	0.258	0.095	0.022	0.015	0.101	0.241	0.704	0.820
Jackknife	0.926	0.901	0.553	0.335	0.152	0.005	0.044	0.177	0.827	0.886

Panel B: Market-model abnormal returns based on trade-to-trade returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.986	0.963	0.418	0.185	0.060	0.084	0.218	0.419	0.979	0.999
CDA	0.448	0.227	0.032	0.014	0.003	0.042	0.054	0.067	0.219	0.450
GST	1.000	1.000	0.999	0.891	0.057	0.050	0.966	1.000	1.000	1.000
GST(BH)	1.000	1.000	0.995	0.873	0.040	0.054	0.953	1.000	1.000	1.000
Rank	0.851	0.748	0.317	0.172	0.020	0.020	0.166	0.319	0.707	0.814
Jackknife	0.131	0.232	0.297	0.293	0.178	0.001	0.006	0.016	0.088	0.081

Table 6 continued

Panel C: Market-adjusted abnormal returns based on lumped returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.983	0.948	0.267	0.098	0.026	0.103	0.233	0.480	0.992	1.000
CDA	0.374	0.159	0.014	0.005	0.001	0.066	0.093	0.131	0.372	0.520
GST	1.000	0.995	0.708	0.459	0.236	0.254	0.517	0.761	0.999	1.000
GST(BH)	1.000	1.000	1.000	0.890	0.053	0.059	0.937	1.000	1.000	1.000
Rank	0.851	0.732	0.258	0.095	0.022	0.015	0.101	0.241	0.704	0.820
Jackknife	0.953	0.936	0.614	0.396	0.178	0.005	0.040	0.176	0.832	0.894

Panel D: Market-model abnormal returns based on lumped returns

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Patell	0.984	0.962	0.435	0.211	0.071	0.068	0.176	0.344	0.965	0.999
CDA	0.459	0.296	0.066	0.034	0.018	0.037	0.051	0.062	0.191	0.391
GST	1.000	1.000	0.998	0.853	0.041	0.069	0.976	1.000	1.000	1.000
GST(BH)	1.000	1.000	1.000	0.936	0.040	0.055	0.987	1.000	1.000	1.000
Rank	0.851	0.754	0.322	0.165	0.026	0.023	0.168	0.326	0.707	0.815
Jackknife	0.115	0.227	0.310	0.295	0.113	0.001	0.001	0.011	0.075	0.064

Table 7
Rejection rates with a stock-return variance increase on day zero, 1988-2006

The stocks are ordinary share issues; data come from Datastream. We randomly sample from the available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. To simulate a stock-price reaction, we add a seeded return to the stock return on the selected event date (day 0). To simulate a variance increase on day zero, we generate a random standard normal value, multiply it by the standard deviation of the stock's estimation-period abnormal return and add the product to the day zero return. Stock returns are trade-to-trade. The market index is the country-specific total market index (level one index) of the Datastream Global series, which is value weighted. Market-adjusted return is the stock return minus the market return. The market model is estimated by OLS; market-model abnormal returns are prediction errors. The abnormal returns of three or 11 trading centered on day zero are added to create window cumulative abnormal returns (CAR). The estimation period, for signs, standard deviations and market model parameters, is trading days –256 through –6 relative to the event; ranks for the rank test incorporate days –256 through +6. The null hypothesis of the Patell, standardized cross-sectional (Std. csect.), time-series portfolio standard deviation (CDA) and jackknife tests is that the mean day zero abnormal return or mean CAR is zero. The null hypothesis of the generalized sign test reported as GST is that the fraction of day zero abnormal returns or CARs having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign; when reported as GST(BH), the null is that the mean abnormal compounded (buy-and-hold) window return is zero. The null hypothesis of the rank and standardize rank (Std. rank) tests is that the mean rank in the event window is equal to that in the estimation period. Alternative hypotheses are one tailed. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% success probability, are 3.3% to 6.8%.

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Panel A: Market-adjusted abnormal returns, event day zero										
Patell	0.996	0.995	0.943	0.602	0.133	0.145	0.591	0.940	1.000	1.000
Std. csect.	0.995	0.994	0.854	0.417	0.056	0.048	0.403	0.855	0.995	0.997
CDA	0.740	0.653	0.315	0.159	0.069	0.093	0.206	0.359	0.672	0.746
GST	1.000	1.000	0.638	0.234	0.026	0.109	0.510	0.875	1.000	1.000
Rank	1.000	1.000	0.816	0.396	0.079	0.065	0.396	0.763	1.000	1.000
Std. rank	0.719	0.715	0.654	0.404	0.087	0.049	0.332	0.628	0.677	0.682
Jackknife	0.626	0.621	0.452	0.214	0.043	0.015	0.161	0.384	0.630	0.630
Panel B: Market-model abnormal returns, event day zero										
Patell	0.997	0.996	0.968	0.699	0.140	0.143	0.655	0.967	1.000	1.000
Std. csect.	0.979	0.979	0.875	0.480	0.065	0.048	0.415	0.868	0.977	0.980
CDA	0.757	0.667	0.344	0.185	0.089	0.083	0.185	0.328	0.654	0.736
GST	1.000	0.999	0.578	0.178	0.013	0.227	0.735	0.971	1.000	1.000
Rank	1.000	1.000	0.858	0.474	0.080	0.073	0.450	0.814	1.000	1.000
Std. rank	0.988	0.932	0.612	0.284	0.026	0.070	0.560	0.913	0.999	1.000
Jackknife	0.071	0.121	0.147	0.098	0.024	0.017	0.081	0.137	0.143	0.080
Panel C: Market-adjusted abnormal returns, three-day event window(–1,+1)										
Patell	0.995	0.994	0.689	0.309	0.065	0.099	0.366	0.740	1.000	1.000
Std. csect.	0.994	0.990	0.582	0.254	0.036	0.043	0.273	0.610	0.993	0.996
CDA	0.603	0.459	0.085	0.037	0.009	0.043	0.088	0.168	0.535	0.621
GST	1.000	0.998	0.675	0.320	0.085	0.179	0.488	0.819	1.000	1.000
GST(BH)	1.000	1.000	0.993	0.767	0.045	0.047	0.807	0.998	1.000	1.000
Rank	1.000	0.956	0.482	0.208	0.043	0.040	0.164	0.411	0.953	0.999
Std. rank	0.696	0.694	0.456	0.196	0.056	0.044	0.157	0.403	0.691	0.693
Jackknife	0.613	0.607	0.374	0.174	0.052	0.010	0.084	0.249	0.606	0.621

Table 7 continued

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Panel D: Market-model abnormal returns, three-day event window (–1,+1)										
Patell	0.996	0.995	0.793	0.419	0.087	0.088	0.396	0.788	1.000	1.000
Std. csect.	0.976	0.969	0.653	0.306	0.053	0.031	0.265	0.602	0.974	0.977
CDA	0.625	0.506	0.128	0.063	0.022	0.033	0.067	0.128	0.490	0.598
GST	1.000	0.999	0.633	0.294	0.056	0.278	0.698	0.929	1.000	1.000
GST(BH)	1.000	1.000	0.995	0.867	0.035	0.046	0.955	1.000	1.000	1.000
Rank	0.999	0.967	0.535	0.230	0.036	0.038	0.212	0.471	0.962	0.998
Std. rank	0.923	0.840	0.317	0.144	0.022	0.063	0.226	0.488	0.931	0.981
Jackknife	0.072	0.125	0.139	0.106	0.046	0.012	0.041	0.078	0.129	0.078
Panel E: Market-adjusted abnormal returns, 11-day event window (–5,+5)										
Patell	0.984	0.922	0.257	0.102	0.032	0.106	0.235	0.444	0.982	1.000
Std. csect.	0.976	0.871	0.238	0.104	0.032	0.062	0.173	0.354	0.947	0.988
CDA	0.327	0.117	0.013	0.003	0.001	0.064	0.091	0.122	0.340	0.530
GST	1.000	0.959	0.446	0.270	0.127	0.211	0.394	0.614	0.994	1.000
GST(BH)	1.000	1.000	0.991	0.763	0.049	0.055	0.813	0.998	1.000	1.000
Rank	0.786	0.577	0.165	0.067	0.025	0.019	0.072	0.159	0.549	0.758
Std. rank	0.626	0.517	0.153	0.076	0.030	0.026	0.068	0.150	0.503	0.625
Jackknife	0.592	0.560	0.293	0.181	0.097	0.010	0.027	0.079	0.458	0.556
Panel F: Market-model abnormal returns, 11-day event window (–5,+5)										
Patell	0.986	0.959	0.417	0.194	0.067	0.097	0.219	0.420	0.981	0.999
Std. csect.	0.715	0.669	0.234	0.114	0.039	0.025	0.083	0.211	0.681	0.726
CDA	0.451	0.230	0.040	0.011	0.006	0.046	0.056	0.073	0.218	0.444
GST	0.999	0.962	0.522	0.295	0.113	0.227	0.485	0.701	0.998	1.000
GST(BH)	1.000	1.000	0.996	0.874	0.039	0.054	0.954	1.000	1.000	1.000
Rank	0.797	0.596	0.186	0.086	0.028	0.025	0.096	0.180	0.580	0.755
Std. rank	0.638	0.446	0.140	0.073	0.029	0.055	0.129	0.207	0.563	0.734
Jackknife	0.071	0.116	0.153	0.124	0.101	0.009	0.009	0.019	0.059	0.058

Table 8

Country clustering: Rejection rates in 1,000 single-country samples of 100 stocks each, 1988-2006

Each sample contains stocks (ordinary share issues) from a single non-U.S. market; data come from Datastream. We randomly select a market and randomly sample from its available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. Sampling is with replacement. The null hypothesis of the Patell, time-series portfolio standard deviation (CDA) and jackknife tests is that the mean day zero abnormal return or mean CAR is zero. The null hypothesis of the generalized sign test reported as GST is that the fraction of day zero abnormal returns or CARs having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign; when reported as GST(BH), the null is that the mean abnormal compounded (buy-and-hold) window return is zero. The null hypothesis of the rank test is that the mean rank in the event window is equal to that of the estimation period. The estimation period, for signs, standard deviations and market model slope and intercept, is trading days –256 through –6 relative to the event. The market index for market-adjusted and market model abnormal returns is the country-specific Datastream Global Index (level one). Market-adjusted return is stock return minus the market index return. The market model is estimated by ordinary least squares. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% binomial success probability, are 3.3% to 6.8%.

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Panel A: Market-adjusted abnormal returns, event day zero										
Patell	0.996	0.996	0.923	0.609	0.055	0.066	0.609	0.940	1.000	1.000
CDA	0.919	0.872	0.608	0.297	0.024	0.056	0.286	0.638	0.897	0.927
GST	1.000	1.000	0.971	0.754	0.066	0.048	0.768	0.990	1.000	1.000
Rank	1.000	1.000	0.986	0.795	0.053	0.036	0.739	0.990	1.000	1.000
Jackknife	0.965	0.975	0.919	0.708	0.085	0.022	0.570	0.898	0.969	0.964
Panel B: Market-model abnormal returns, event day zero										
Patell	0.998	0.998	0.950	0.688	0.075	0.067	0.641	0.935	1.000	1.000
CDA	0.924	0.888	0.651	0.331	0.035	0.052	0.280	0.615	0.884	0.924
GST	1.000	1.000	0.965	0.766	0.054	0.053	0.855	0.993	1.000	1.000
Rank	1.000	1.000	0.992	0.863	0.052	0.042	0.860	0.990	1.000	1.000
Jackknife	0.489	0.540	0.573	0.486	0.108	0.017	0.305	0.525	0.535	0.483
Panel C: Market-adjusted abnormal returns, three-day event window (–1,+1)										
Patell	0.996	0.990	0.645	0.301	0.056	0.081	0.335	0.727	1.000	1.000
CDA	0.853	0.728	0.300	0.110	0.024	0.046	0.134	0.335	0.825	0.902
GST	1.000	0.999	0.869	0.585	0.181	0.142	0.564	0.895	1.000	1.000
GST(BH)	1.000	1.000	0.980	0.725	0.047	0.047	0.758	0.980	1.000	1.000
Rank	1.000	0.999	0.817	0.448	0.053	0.031	0.386	0.793	1.000	1.000
Jackknife	0.950	0.954	0.770	0.489	0.115	0.020	0.235	0.656	0.949	0.946
Panel D: Market-model abnormal returns, three-day event window (–1,+1)										
Patell	0.998	0.997	0.737	0.390	0.072	0.068	0.376	0.731	1.000	1.000
CDA	0.892	0.787	0.332	0.139	0.035	0.031	0.112	0.303	0.763	0.883
GST	1.000	0.997	0.880	0.656	0.156	0.156	0.698	0.933	1.000	1.000
GST(BH)	1.000	1.000	0.967	0.771	0.045	0.038	0.850	0.991	1.000	1.000
Rank	1.000	1.000	0.860	0.560	0.039	0.031	0.543	0.845	1.000	1.000
Jackknife	0.485	0.537	0.521	0.401	0.159	0.008	0.102	0.311	0.505	0.477

Table 8 continued

Test	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
	Seeded return									
	Lower-tailed rejection rates					Upper-tailed rejection rates				
Panel E: Market-adjusted abnormal returns, 11-day event window (–5,+5)										
Patell	0.958	0.813	0.275	0.142	0.050	0.126	0.259	0.431	0.968	1.000
CDA	0.651	0.445	0.106	0.059	0.022	0.071	0.129	0.194	0.635	0.836
GST	0.996	0.939	0.569	0.366	0.184	0.240	0.417	0.624	0.986	1.000
GST(BH)	1.000	1.000	0.970	0.709	0.048	0.050	0.775	0.994	1.000	1.000
Rank	0.948	0.861	0.367	0.179	0.040	0.028	0.143	0.333	0.849	0.956
Jackknife	0.912	0.861	0.565	0.372	0.190	0.025	0.070	0.189	0.827	0.885
Panel F: Market-model abnormal returns, 11-day event window (–5,+5)										
Patell	0.985	0.898	0.395	0.208	0.057	0.097	0.226	0.410	0.922	0.998
CDA	0.729	0.520	0.142	0.072	0.026	0.044	0.074	0.137	0.496	0.722
GST	0.996	0.955	0.634	0.415	0.196	0.220	0.447	0.661	0.987	1.000
GST(BH)	1.000	1.000	0.952	0.748	0.038	0.045	0.867	0.994	1.000	1.000
Rank	0.952	0.858	0.444	0.243	0.043	0.033	0.240	0.397	0.862	0.953
Jackknife	0.497	0.523	0.448	0.391	0.253	0.008	0.031	0.071	0.358	0.428

Table 9

Rejection rates in the most concentrated non-U.S. stock markets, 1,000 samples

Each sample contains 100 stocks (ordinary share issues) from the ten most concentrated non-U.S. stock markets in 1988–1991, 1992–1994, 1995–1997, 1998–2000, 2001–2003 and 2004–2006. To determine the most concentrated markets in each period, we calculate a Herfindahl index based on each stock's number of shares traded times closing price from Datastream. We pool the data for the identified markets from all periods and randomly sample, with replacement, from the available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. The null hypothesis of the generalized sign test reported as GST is that the fraction of day zero abnormal returns or CARs having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign; when reported as GST(BH), the null is that the mean abnormal compounded (buy-and-hold) window return is zero. The null hypothesis of the rank test is that the mean rank in the event window is equal to that of the estimation period. The estimation period, for signs, standard deviations and market model slope and intercept, is trading days –256 through –6 relative to the event. Returns are trade-to-trade. The market index for market-adjusted and market model abnormal returns is the country-specific Datastream Global Index (level one). Market-adjusted return is stock return minus the market index return. The market model is estimated by ordinary least squares. For event windows, we conduct the GST on abnormal buy-and-hold returns and the rank test on cumulative abnormal returns. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% binomial success probability, are 3.3% to 6.8%.

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Panel A: Market-adjusted returns, event day zero										
GST	1.000	1.000	1.000	0.957	0.064	0.055	0.976	1.000	1.000	1.000
Rank	1.000	1.000	1.000	0.933	0.045	0.047	0.928	1.000	1.000	1.000
Panel B: Market model abnormal returns, event day zero										
GST	1.000	1.000	1.000	0.999	0.038	0.039	1.000	1.000	1.000	1.000
Rank	1.000	1.000	1.000	0.999	0.048	0.048	0.998	1.000	1.000	1.000
Panel C: Market-adjusted returns, event window (–1,+1)										
GST(BH)	1.000	1.000	1.000	0.955	0.036	0.052	0.983	1.000	1.000	1.000
Rank	1.000	1.000	0.937	0.593	0.043	0.061	0.624	0.940	1.000	1.000
Panel D: Market model abnormal returns, event window (–1,+1)										
GST(BH)	1.000	1.000	1.000	1.000	0.029	0.044	1.000	1.000	1.000	1.000
Rank	1.000	1.000	0.978	0.898	0.044	0.057	0.913	0.978	1.000	1.000
Panel E: Market-adjusted returns, event window (–5,+5)										
GST(BH)	1.000	1.000	1.000	0.959	0.030	0.055	0.980	1.000	1.000	1.000
Rank	0.945	0.882	0.498	0.215	0.042	0.064	0.277	0.541	0.901	0.948
Panel F : Market model abnormal returns, event window (–5,+5)										
GST(BH)	1.000	1.000	1.000	1.000	0.028	0.044	1.000	1.000	1.000	1.000
Rank	0.922	0.889	0.654	0.472	0.065	0.077	0.476	0.673	0.893	0.932

Table 10

Rejection rates for markets with the most non-normally distributed returns

Each sample contains 100 stocks (ordinary share issues) randomly selected with replacement from the ten non-U.S. stock markets where stock return distributions deviate most from normality in 1988–1991, 1992–1994, 1995–1997, 1998–2000, 2001–2003 and 2004–2006. To determine the most non-normal markets, we calculate the Jarque-Bera test statistic for non-normality, *J*, over each period for each stock that has at least 100 trading days of non-missing returns in the period, and rank markets by median *J*. We pool the data for the identified markets from all periods and randomly sample, with replacement, from the available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. The null hypothesis of the generalized sign test reported as GST is that the fraction of day zero abnormal returns or CARs having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign; when reported as GST(BH), the null is that the mean abnormal compounded (buy-and-hold) window return is zero. The null hypothesis of the rank test is that the mean rank in the event window is equal to that of the estimation period. The estimation period, for signs, standard deviations and market model slope and intercept, is trading days –256 through –6 relative to the event. Returns are trade-to-trade. The market index for market-adjusted and market model abnormal returns is the country-specific Datastream Global Index (level one). Market-adjusted return is stock return minus the market index return. The market model is estimated by ordinary least squares. For event windows, we conduct the GST on abnormal buy-and-hold returns and the rank test on cumulative abnormal returns. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% binomial success probability, are 3.3% to 6.8%.

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Panel A: Market-adjusted returns, event day zero										
GST	1.000	1.000	1.000	0.953	0.043	0.045	0.978	1.000	1.000	1.000
Rank	1.000	1.000	1.000	0.925	0.048	0.050	0.924	1.000	1.000	1.000
Panel B: Market model abnormal returns, event day zero										
GST	1.000	1.000	1.000	0.999	0.034	0.053	1.000	1.000	1.000	1.000
Rank	1.000	1.000	1.000	0.998	0.040	0.053	0.999	1.000	1.000	1.000
Panel C: Market-adjusted returns, event window (–1,+1)										
GST(BH)	1.000	1.000	1.000	0.958	0.041	0.049	0.972	1.000	1.000	1.000
Rank	1.000	0.999	0.924	0.576	0.053	0.048	0.618	0.933	1.000	1.000
Panel D: Market model abnormal returns, event window (–1,+1)										
GST(BH)	1.000	1.000	1.000	0.998	0.038	0.036	1.000	1.000	1.000	1.000
Rank	1.000	1.000	0.984	0.895	0.044	0.058	0.904	0.985	1.000	1.000
Panel E: Market-adjusted returns, event window (–5,+5)										
GST(BH)	1.000	1.000	1.000	0.950	0.045	0.077	0.983	1.000	1.000	1.000
Rank	0.930	0.865	0.460	0.223	0.047	0.062	0.283	0.555	0.907	0.952
Panel F : Market model abnormal returns, event window (–5,+5)										
GST(BH)	1.000	1.000	1.000	0.999	0.026	0.052	1.000	1.000	1.000	1.000
Rank	0.918	0.866	0.615	0.420	0.048	0.084	0.494	0.690	0.909	0.942

Table 11

Rejection rates with market-moving events in 1,000 concentrated-market samples

Each sample contains 100 stocks (ordinary share issues) from the ten most concentrated non-U.S. stock markets in 1988–1991, 1992–1994, 1995–1997, 1998–2000, 2001–2003 and 2004–2006. To determine the most concentrated markets in each period, we calculate a Herfindahl index based on each stock's number of shares traded times closing price from Datastream. We pool the data for the identified markets from all periods and randomly sample, with replacement, from the available stock-listing day combinations; a listing day is when the market is open and the stock is listed for trading, subject to data availability screens. To simulate market-moving events, we find f_{MV}, the four-week moving average ratio, on day zero, of each stock's market value to the total value of stocks in its market. We multiply the seeded return by the stock's f_{MV} and add the product to the market index return before calculating the stock's abnormal return. The null hypothesis of the generalized sign test reported as GST is that the fraction of day zero abnormal returns or CARs having a particular sign is equal to the fraction of estimation-period abnormal returns with that sign; when reported as GST(BH), the null is that the mean abnormal compounded (buy-and-hold) window return is zero. The null hypothesis of the rank test is that the mean rank in the event window is equal to that of the estimation period. The estimation period, for signs, standard deviations and market model slope and intercept, is trading days –256 through –6 relative to the event. Returns are trade-to-trade. The market index for market-adjusted and market model abnormal returns is the country-specific Datastream Global Index (level one). Market-adjusted return is stock return minus the market index return. The market model is estimated by ordinary least squares. For event windows, we conduct the GST on abnormal buy-and-hold returns and the rank test on cumulative abnormal returns. The 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial are 3.7% to 6.4%; the 99% limits, still with a 5% binomial success probability, are 3.3% to 6.8%.

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	Lower-tailed rejection rates					Upper-tailed rejection rates				
Panel A: Market-adjusted returns, event day zero										
GST	1.000	1.000	1.000	0.957	0.064	0.055	0.976	1.000	1.000	1.000
Rank	1.000	1.000	1.000	0.933	0.045	0.047	0.928	1.000	1.000	1.000
Panel B: Market model abnormal returns, event day zero										
GST	1.000	1.000	1.000	0.999	0.050	0.057	1.000	1.000	1.000	1.000
Rank	1.000	1.000	1.000	0.999	0.048	0.048	0.998	1.000	1.000	1.000
Panel C: Market-adjusted returns, event window (–1,+1)										
GST(BH)	1.000	1.000	1.000	0.952	0.036	0.053	0.986	1.000	1.000	1.000
Rank	1.000	1.000	0.937	0.593	0.043	0.061	0.624	0.940	1.000	1.000
Panel D: Market model abnormal returns, event window (–1,+1)										
GST(BH)	1.000	1.000	1.000	0.998	0.041	0.071	1.000	1.000	1.000	1.000
Rank	1.000	1.000	0.978	0.898	0.044	0.057	0.913	0.978	1.000	1.000
Panel E: Market-adjusted returns, event window (–5,+5)										
GST(BH)	1.000	1.000	1.000	0.959	0.036	0.051	0.974	1.000	1.000	1.000
Rank	0.945	0.882	0.498	0.215	0.042	0.064	0.277	0.541	0.901	0.948
Panel F : Market model abnormal returns, event window (–5,+5)										
GST(BH)	1.000	1.000	1.000	1.000	0.048	0.064	1.000	1.000	1.000	1.000
Rank	0.922	0.889	0.654	0.472	0.065	0.077	0.476	0.673	0.893	0.932

Table 12

Stock-price reactions to non-U.S. cross-country merger and acquisition announcements, 1988-2006

The sample contains cross-country non-U.S. merger and acquisition announcements from 1988-2006. Day zero is the announcement date as reported by Thomson One Banker. We exclude mergers and acquisitions occurring among financial companies (SIC code 6000) and include deals with a percentage of shares sought above 49%. The estimation period ends 46 trading days before day zero and is 255 days long. Returns are trade-to-trade. The market index for market-adjusted and market model abnormal returns is the country-specific Datastream Global Index (level one). AR denotes market-adjusted or market-model abnormal return; for multi-day windows, CAR denotes cumulative abnormal return and BHAR, buy-and-hold abnormal return. Market-adjusted return is stock return minus market index return. The market model is estimated by ordinary least squares. For multi-day windows, we conduct the GST on abnormal buy-and-hold returns and the rank test on cumulative abnormal returns.

Event window (trading days)	Number of events	Mean AR or CAR	Median AR or CAR	Mean BHAR	Median BHAR	Positive: negative AR or CAR	Positive: negative BHAR	Rank *Z*	GST *Z* (of BHAR if multi-day)
Panel A: Market-adjusted returns, target firms									
0	202	9.08%	3.98%	NA	NA	148:54	NA	7.869***	7.227***
(-1,+1)	220	12.16%	6.78%	12.41%	6.47%	167:53	168:52	7.234***	8.462***
(-5,+5)	222	14.83%	10.49%	15.38%	10.04%	172:50	170:52	4.662***	8.564***
Panel B: Market model abnormal returns, target firms									
0	202	7.75%	3.17%	NA	NA	144:58	NA	7.714***	7.855***
(-1,+1)	220	10.23%	6.61%	10.17%	6.20%	161:59	161:59	6.992***	8.764***
(-5,+5)	222	8.24%	8.92%	2.69%	8.61%	159:63	157:65	4.675***	8.064***
Panel C: Market-adjusted returns, acquiring firms									
0	252	-0.48%	-0.22%	NA	NA	112:140	NA	-1.543	-1.331
(-1,+1)	262	0.56%	-0.14%	0.51%	-0.22%	125:137	124:138	-0.413	-0.423
(-5,+5)	263	1.52%	0.14%	1.41%	-0.08%	136:127	131:132	-0.491	0.381
Panel D: Market model abnormal returns, acquiring firms									
0	252	-0.64%	-0.21%	NA	NA	110:142	NA	-1.524	-0.738
(-1,+1)	262	-0.29%	-0.11%	-0.48%	-0.15%	125:137	123:139	-0.534	0.318
(-5,+5)	263	-2.01%	-0.75%	-5.67%	-0.72%	117:146	113:150	-1.206	-0.976

*** denotes statistical significance at 1% using a one-tail test.

Figure 1

Day zero rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006

The percentage of 1,000 randomly formed portfolios of 100 securities each in which the null hypothesis of zero abnormal returns (vertical axis) is rejected at different levels of seeded abnormal return (horizontal axis). Abnormal returns are calculated by the market-adjusted method using trade-to-trade returns. The 3.7% and 6.4% rejection rates are the 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

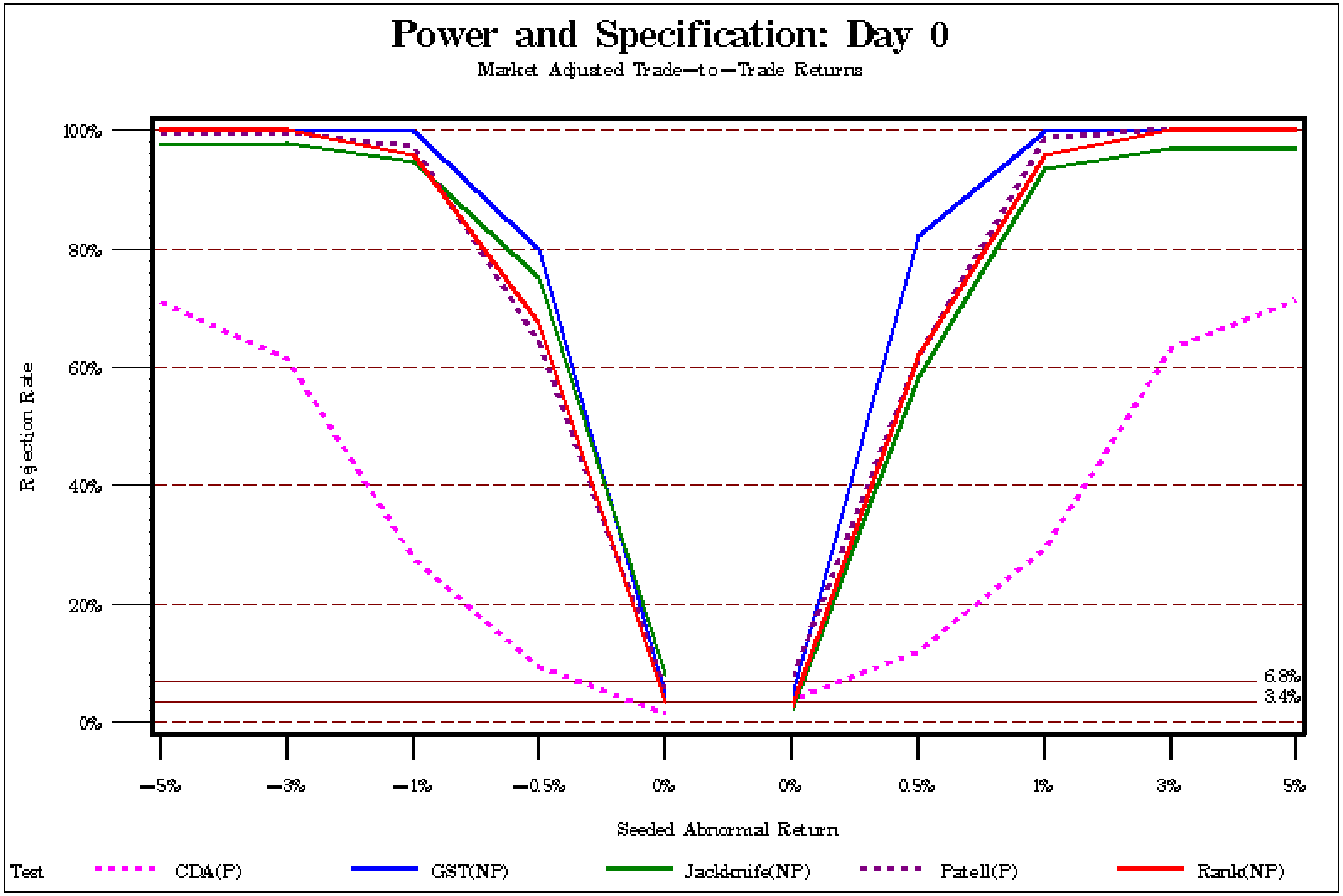

Figure 2

Three-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006

The percentage of 1,000 randomly formed portfolios of 100 securities each in which the null hypothesis of zero abnormal returns (vertical axis) is rejected at different levels of day 0 seeded abnormal return (horizontal axis) for a three-day window centered on day zero. Abnormal returns are calculated by the market-adjusted method using trade-to-trade returns. The 3.7% and 6.4% rejection rates are the 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

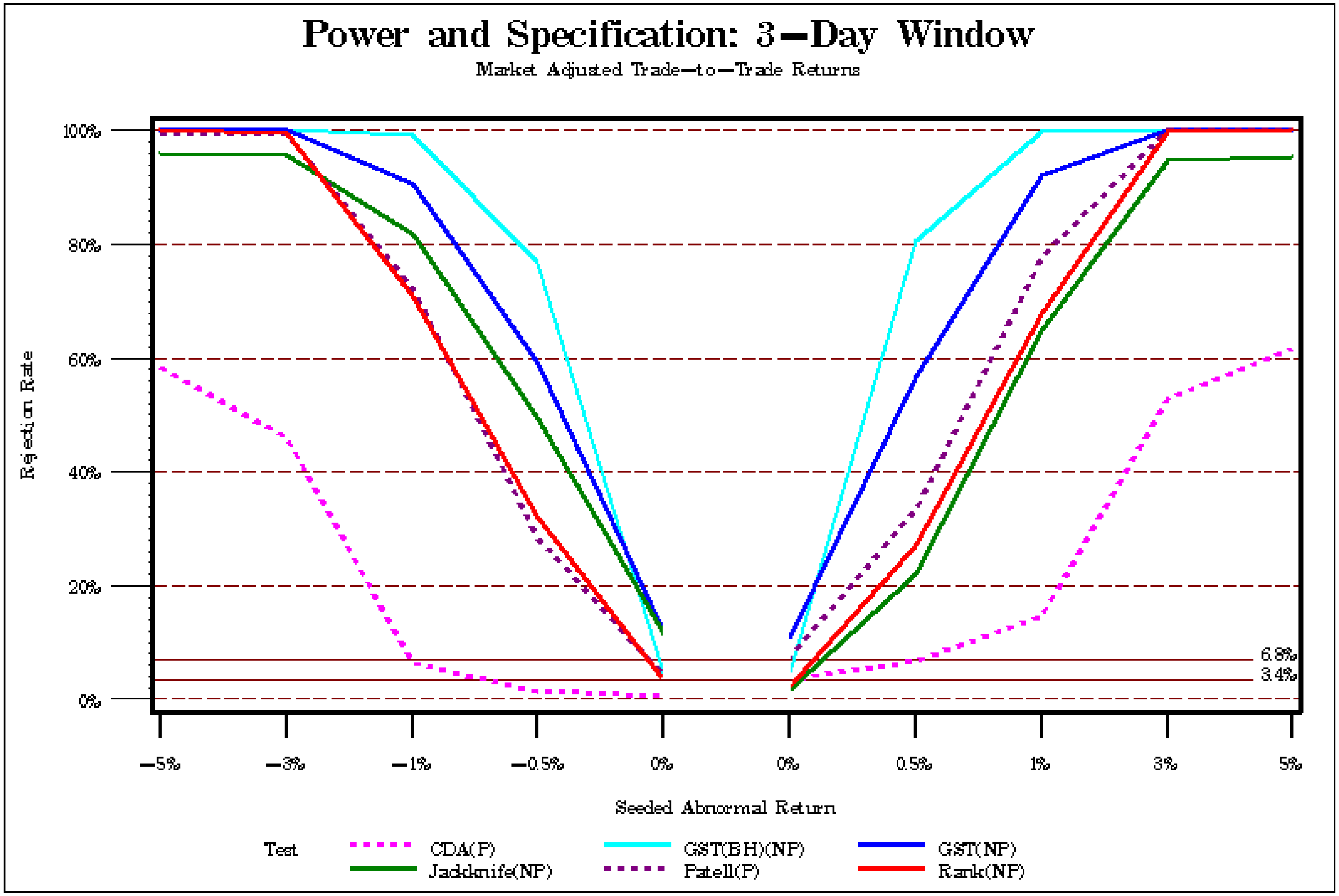

Figure 3

Eleven-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006

The percentage of 1,000 randomly formed portfolios of 100 securities each in which the null hypothesis of zero abnormal returns (vertical axis) is rejected at different levels of day 0 seeded abnormal return (horizontal axis) for an eleven-day window centered on day zero. Abnormal returns are calculated by the market-adjusted method using trade-to-trade returns. The 3.7% and 6.4% rejection rates are the 95% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.