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MULTI-COUNTRY EVENT STUDY METHODS

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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 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 to limiting the samples to situations expected to be problematic for test specification or power. Applying the tests that perform best in simulation to merger announcements produces reasonable results.

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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 study methods with multi-country data is growing rapidly.

Stock markets differ on many dimensions, e.g., 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. Conclusions regarding the performance of event-study tests that appear in the methodological literature are based on simulated samples from single, mostly advanced markets. The applicability of these conclusions to actual samples that combine stocks from multiple diverse national markets is an unexplored empirical question. Compared to U.S. data, commonly used test statistics may be less powerful and may be biased, leading to potentially incorrect inferences.

We analyze the performance of event-study methods when applied to non-U.S. multi-country samples. Return distributions in such samples are severely non-normal, even at the portfolio level. We use the simulation approach pioneered by Brown and Warner (1980, 1985) to investigate the accuracy and power of several statistical tests from the literature, using the market-adjusted and market-model benchmark methods. Consistent with serious 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. In random samples, the rank test does not reject a true null too often 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 in samples that are potentially problematic for test specification or power. These include single-market samples, samples from the most concentrated national markets and markets with the most non-normally distributed returns. We also examine the ability of the two tests to detect abnormal returns when the affected securities are potential "market movers." This is when a stock can make up such a large fraction of its local market's overall capitalization that the individual price effects of firm-specific information arrivals exert a significant influence on the market index. Thus, abnormal returns calculations that use the local market index would deduct the part of the information effect included in the index return from the total information effect in the stock return, potentially reducing power. When we simulate such effects, we find that the rank and generalized sign tests continue to exhibit correct specification and good power.

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. Literature review

Starting from Fama, Fisher Jensen and Roll (1969) seminal study of stock splits, event study methods became increasingly popular to gauge the effect of information arrival on the stocks market value and on traded volume. The usefulness of this methodology comes from the assumption that the financial market is efficient and market participant are rational. Consequently, the information conveyed by an event will be promptly impounded into prices, as the investors react to the new information arrival. The method can be used for firm-specific as well as economy-wide events as mergers and acquisitions, dividends and earnings announcements, announcement regarding macroeconomic factors and aggregates. Brown and Warner (1980, 1985) are among the first to consider the how the statistical properties of monthly and daily stock return affect the applicability and the performance of event study methods and how it is possible to accommodate more specific hypotheses. In short-term event study, if on the one hand the use of high frequency data allows the researcher to rely on a great amount of information, on the other several potential issues need to be considered. The following subsections describe in details some of the most common methodological issues in short-term event studies.

2.1 The departure from normality of stock returns

Increasing the frequency in the time series of stock returns leads to a substantial departure from the normality assumption. On a sample of NYSE and AMEX stocks, Brown and Warner (1985), show that at security level daily returns and abnormal returns are highly non-normal. Skewness and kurtosis are respectively 0.99 and 6.87, noticeably greater than what is expected under the normality assumption. Using portfolio level data, the departure from normality becomes less and less pronounced and it is almost neglectable for portfolios of 50 securities. Therefore, it seems that the distribution of returns converges to normality rather quickly.

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 kurtosis of 26.51. Campbell and Wasley (1993) report, for Nasdaq securities, average skewness and kurtosis for single-security market model returns of 0.96 and 16.98 from

12/14/1973 through 12/20/1987. At portfolio level, for portfolios of 100 Nasdaq stocks, the raw and abnormal returns are instead normally distributed.

Those finding suggest that the performance of event study methods can be sensitive to the sample size, and therefore small sample properties of the test statistics used should be carefully considered.

Anyhow, event study methods traditionally rely on cross-sectional mean of excess returns, thus the normality assumption is of concern when the cross-sectional mean excess returns departs from the normality assumption. Following the Central Limit Theorem (Billingsley, 1979) if the abnormal returns in the cross-section of securities are independent and identically distributed drawings from finite variance distributions, then the distribution of the sample mean excess return converges to normality as the number of securities increases. Brown and Warner (1985) findings support the Central Limit Theorem and indicate that increasing the sample size to portfolios of 50 securities the mean abnormal return seems close to normal. They conclude that non-normality has no significant impact on the applicability of event study methods: increasing the number of securities in the portfolio, the mean excess return in a cross-section of securities converges to normality and standard parametric tests (relying on the normality assumption) are well-specified. Although, Brown and Warner (1985) results are sensitive to the trading frequency of the market, the power of the investigated test statistic being consistently greater in samples of NYSE securities, rather than AMEX securities. Markets characterized by severe frictions in their trading, as infrequent trading, wide bid-ask spreads, lead to delays in the price update. Those markets are characterized by a relatively higher frequency of zero-returns as well as frequent price reversals (i.e. extreme returns). The frequency of zero and extreme returns in the time series of the security affect how severe is the departure from the normality assumption. Empirical papers dealing with samples characterized by infrequent trading demonstrate that the performance of the test statistics that assume the normal distribution of stock returns (i.e. the parametric tests) is impaired by the magnitude of the departure from the normal distribution. When non normality is severe, non-parametric test should be used to test the significance of the abnormal performance. Cowan and Sergeant (1996) and Campbell and Wasley (1993) report that traditional parametric tests based on standardized abnormal returns are mis-specified for thinly traded (non-normal) samples, while the Corrado's non parametric test based on abnormal returns' ranks is both well-specified and powerful.

2.2 Time-series dependence and non-synchronous trading

When the return on a security and the return on the market index have different trading frequencies, ordinary least squares (OLS) estimates of market model parameters are biased and inconsistent, especially for high-frequency data (Scholes and Williams, 1977; Dimson, 1979). As an example, the daily prices of stocks commonly employed in short term event study are "closing prices", which do not generally occur at the same time each day, but the implicit assumption in the use of those prices is that they are registered at 24-hours intervals from each other. Trading frictions can have a different impact on the measurement error depending on the volume traded. The price adjustment delays enhance serial cross sectional dependence in observed returns which contributes to bias the market model parameters' estimate. The Scholes and Williams procedure consider non-synchronous trading in the estimation of the beta. Instead of employing a single beta estimate, the procedure employs the lead, the lag and the current value of the market index to estimate three beta coefficients. The beta used in the estimate of the abnormal return is calculated as the sum of the three coefficients over one plus twice the estimation period first order auto-correlation coefficient of the market index. By introducing leads and lags of the market index, the procedure should capture the sensitivity of stock returns to contemporaneous market returns, as well as leads and lags. However, Brown and Warner (1985) find no mis-specification in the event study methodology even when betas are biased. Methodologies based on the procedures suggested by Scholes and Williams (1977) and Dimson (1979) do seem to reduce biases in OLS estimates, but the specification and power of the actual tests for abnormal performance is similar to that obtained with the OLS market model. Since, the use of the market model to estimate the beta is not carried out to draw inference on the value nor on the significance of the coefficient, but instead it address the problem of expunging the normal or expected return from the security observed return, the potential for a bias in the beta estimate is not of concern. Campbell and Wasley (1993) and Cowan and Sergeant (1996) report that for daily data and short event windows the event study test specification and power are not altered by the use of Scholes-Williams versus OLS estimation.

Even if non synchronous trading do not affect the performance of the test statistics, the resulting serial correlation of stock returns might bias the variance estimates when testing the hypothesis on event windows cumulative abnormal returns rather than single-day abnormal returns. Brown and Warner (1985) find no significant impact of serial correlation in the performance of the method.

2.3 Variance Increase

The variance of daily returns is rarely stationary around an event. The information arrival might be processed with delays by the investors on the market, or the new information might change the systematic risk of the stocks, leading in both cases to an increase in the observed variance. On other words, the security reaction to an informative vent might be different across our security portfolio. Without any adjustment for the volatility induced by the event, the variance estimated in the estimation period is likely to understate the true variance. Brown and Warner (1985) report that test relying on the cross-sectional variance of abnormal returns are well specified for event date variance increases but not very powerful. Boehmer, Musumeci and Poulsen (1991) report that the standardized cross-sectional test is more powerful and well specified. Although, the test is assuming a homogeneous increase in variance due to the event. Savickas (2003) address the problem of conditional heteroskedasticity in the variance and the event-induced variance increase by adoption of a GARCH-based approach that models the volatility process and event induced variance increase. Cowan (1992) reports that the generalized sign test also is well specified for event date variance increases and more powerful than the cross-sectional test.

3. Recent multi-country event studies

Table 1 summarizes 18 recent articles in accounting, economics, finance, insurance and marketing journals that apply event-study methods to multi-country samples. We do not claim that this is an exhaustive list, nor is it our intention to criticize the articles. Our purpose is to survey current practice to motivate and provide context for our simulation work, and to make recommendations for future research.

The 18 articles in Table 1 report relatively simple methods for identifying a benchmark or "normal" return. Nine use only a single-index market model, five report only market-adjusted returns (where the market index return is the proxy for a normal stock return), and one reports only the comparison-period method, which assumes a constant mean that under the null hypothesis is equal to the estimation-period mean. The remaining studies report parallel sets of results using two benchmark approaches. Two report the market model and market-adjusted returns; one reports the market model and a constant mean model. 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, 16 of the 18 studies in Table 1 report at least one parametric test, one reports significance levels but does not indicate how they are obtained and one reports only point estimates without a test. Of the 16 that report one or more tests, five 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). Four studies report a parametric test based on standardized abnormal returns, introduced by Patell (1976) and also explained by Mikkelson and Partch (1986). Another article reports a version of the Patell test, introduced by Boehmer, Musumeci and Poulsen (1991), that incorporates an adjustment for time-varying standard errors. Five papers report 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.

Seven of the 16 papers that report a parametric test also report a non-parametric test. Three use the Wilcoxon signed rank test, one uses the rank test for event studies introduced by Corrado (1989), and three use 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, 1992). All 18 studies in Table 1 obtain non-U.S. return data from Thomson Reuters Datastream.

4. Data and methods

4.1 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 identifies both active and dead (delisted) equities in Datastream. 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 think is 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).

4.2 Return and abnormal return calculations

4.2.1 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 suggest that lumped returns, by increasing the number of return observations, can improve the efficiency of estimators and test statistics used in event studies.

4.2.2 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

[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.

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

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

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

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

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

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

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

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

4.3 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 random-number 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.

[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.

4.4 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 (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

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

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 the market model, the estimated standard deviation 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

$$s_{i(est)} = \sqrt{\frac{1}{M_i - 1} \sum_{t=-256}^{-6} (u_{it} - \bar{u}_i)^2}, \tag{9}$$

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

For three- and 11-day event windows the Patell test statistic is:[3]

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

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

$$t_{CDA} = \bar{u}_t / s(\bar{u}_t), \tag{11}$$

[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.

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

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

$$s(\overline{u}_t) = \sqrt{(1/250)\sum_{t=-256}^{-6} (\overline{u}_t - \overline{\overline{u}})^2}, \tag{12}$$

where $\overline{\overline{u}} = (1/251)\sum_{t=-256}^{-6} \overline{u}_t$. 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

$$t_{CDA(T_1,T_2)} = CAAR(T_1,T_2) / \sqrt{(T_2 - T_1)} \times s(\overline{u}_t). \tag{13}$$

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

$$Z_t = \frac{\left(\frac{N(T-2)}{T-4}\right)^{-1/2} \sum_{i=1}^{N} (u_{it} / s_i)}{s_t}, \tag{14}$$

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

$$\sqrt{[1/(N-1)]\sum_{i=1}^{N} (u_{it} - \overline{u}_t)^2}, \tag{15}$$

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,

$$SCAR_i\left(T_1,T_2\right)=CAR_i\left(T_1,T_2\right)\big/s_{CAR_i\left(T_1,T_2\right)}, \tag{16}$$

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

$$s_{CAR_i\left(T_1,T_2\right)}=W_i^{1/2}s_i, \tag{17}$$

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

$$s_{CAR_i\left(T_1,T_2\right)}=s_i\left[W_i+\frac{W_i^2}{M_i}+\frac{\sum_{t=T_1}^{T_2}(R_{mt}-W_i\bar{R}_m)^2}{\sum_{t=-256}^{-6}(R_{mt}-\bar{R}_m)^2}\right]^{1/2}. \tag{18}$$

The standardized cross-sectional statistic for the window is

$$Z_t=\frac{\sum_{i=1}^{N}SCAR_i\left(T_1,T_2\right)}{\sqrt{N}s_{SCAR}}, \tag{19}$$

where

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

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 seeds, 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 $M_i \leq 251$ 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, a commonly used alternative to the generalized sign test. Unlike the generalized sign test, which relies on the frequency of positive or negative returns, Corrado's rank test transforms each security's time series of abnormal returns into their respective ranks This test is also 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_{i0} 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

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

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_{i0} 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 for portfolios of U.S. securities. 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

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

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

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

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.

5. Results

5.1 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). Statistics for the U.S. market, which is not in the sample, are shown for comparison; U.S. data come from CRSP. 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.

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. The overall average standard deviation, skewness and excess kurtosis are several times the corresponding statistics for the U.S. The results in Table 2 indicate that individual equity returns in multi-country, non-U.S.-

dominated samples generally are more volatile and diverge from a normal distribution substantially farther than in U.S. 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 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 kurtosis for market model abnormal returns of 0.96 and 16.98 from December 14, 1973 through December 20, 1987.

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

[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.

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.

5.2 Simulations with multi-country random samples

Table 4 and Figure 1 present 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 the upper 99% confidence limit of 6.8%.

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 with 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 show 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 returns 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 reports 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.

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.

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.

5.3 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% in the lower tail and upper tail, respectively). The standardized cross-sectional test is correctly specified but less powerful than the Patell test. 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.

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.

5.4 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 (e.g. Brown and Warner 1980, 1985) 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. 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. However, there is noticeable improvement in the power of the CDA compared to the simulation results using multi-country samples. This implies that multi-country samples should be tested differently than single country samples. Also, in single-country samples the parametric CDA test may be a decent alternative to the GST and rank statistics. 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.

5.5 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]

[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 advanced 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.

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.

5.6 Samples from markets with the most non-normal returns

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.

5.7 Samples from the most concentrated markets in the case of market-moving events

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 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]

6. 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. Atkas, de Bodt and Roll (2007) report 11-day announcement window returns that

[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.

are insignificant for bidders and 9% (significant) for targets in a multi-country sample of proposed mergers and acquisitions submitted to the European Commission for approval over 1990–2000.

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 or target 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 the studies cited above, 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.

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.

7. 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 substantially 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 doubling of variance on the event date, significant results from the tests should be interpreted with caution.

Apart from the selection of a test statistic, trade-to-trade returns and 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.

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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 reporting event-study results for international samples. If event-study results for multiple samples appear in an article, N is the main sample size.

Journals: AE: Applied Economics; EMR: Emerging Markets Review; EFM: European Financial Management; EJ: Economic Journal; JAE: Journal of Accounting and Economics; JBF: Journal of Banking and Finance; 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; JM: Journal of Marketing; JRI: Journal of Risk and Insurance; RFS: Review of Financial Studies.

Models: CP: constant mean based on estimation (comparison) period; MM: market model abnormal returns; MAR; market-adjusted returns.

Index and currency: L: local market index or currency; G: global market index; R; regional (multi-country) market index; C: converted to express returns in a single currency.

Tests: CDA: crude dependence adjustment, i.e. the portfolio time-series standard deviation based t-test of Brown and Warner (1980, 1985); Corrado rank: Corrado (1986); GST: generalized sign (null states that percent positive in event window and estimation period are equal); Patell: Patell (1976) standardized abnormal return Z; signed rk: Wilcoxon signed-rank; std. csect.: standardized cross-sectional; "t": article indicates t-test without further distinction.

Miscellaneous: Eur: reported as "various European countries"; NA: not applicable; NR: not reported.

Article	N	Countries	Model	Index	Curr.	Windows	Tests	Estimation period
Atkas, de Bodt and Roll (2007), EJ	290	NR	MM	L	C	(-5, +5)	Std. csect.	(-200, -30)
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
Fields, Fraser and Kolari (2007), JRI	129	NR	CP	L	L	(-1, 0)	Patell, GST	(-200, -51)
Forbes (2004), JIE	21,651	46	MM	G	L	Two weeks, 12 weeks	None used	one year
Gielens, Van de Gucht, Steenkamp and Dekimpe (2008), JM	98	Eur	MM, CP	L	L	(0, +1), (+2, +5), (+2, +10) …	Patell	(–260, –10)
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
Melvin and Valero (2009), EFM	146	21	MM	L	L	(-5,-1), (0,0), (-5,+5) …	Patell, GST	(–180, –31)
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

Table 2

Descriptive statistics of daily trade-to-trade returns of individual equities in 54 sample 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. The U.S., for which data come from CRSP using the above inclusion criteria, is shown for comparison; it is not in the sample analyzed in this paper nor in the overall statistics below.

				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
U.S.	18,523	1932	NA	0.001	0.000	0.000	0.049	1.327	25.732	27.7%
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	Excess 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

Test	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
	Seeded return									
	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

	Seeded return									
	–5%	–3%	–1%	–0.5%	0%	0%	0.5%	1%	3%	5%
Test	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, three-day 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 three-day 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,11-day 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, 11-day 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, three-day 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, three-day 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, 11-day 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, 11-day 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, three-day 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, three-day 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, 11-day 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, 11-day 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 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

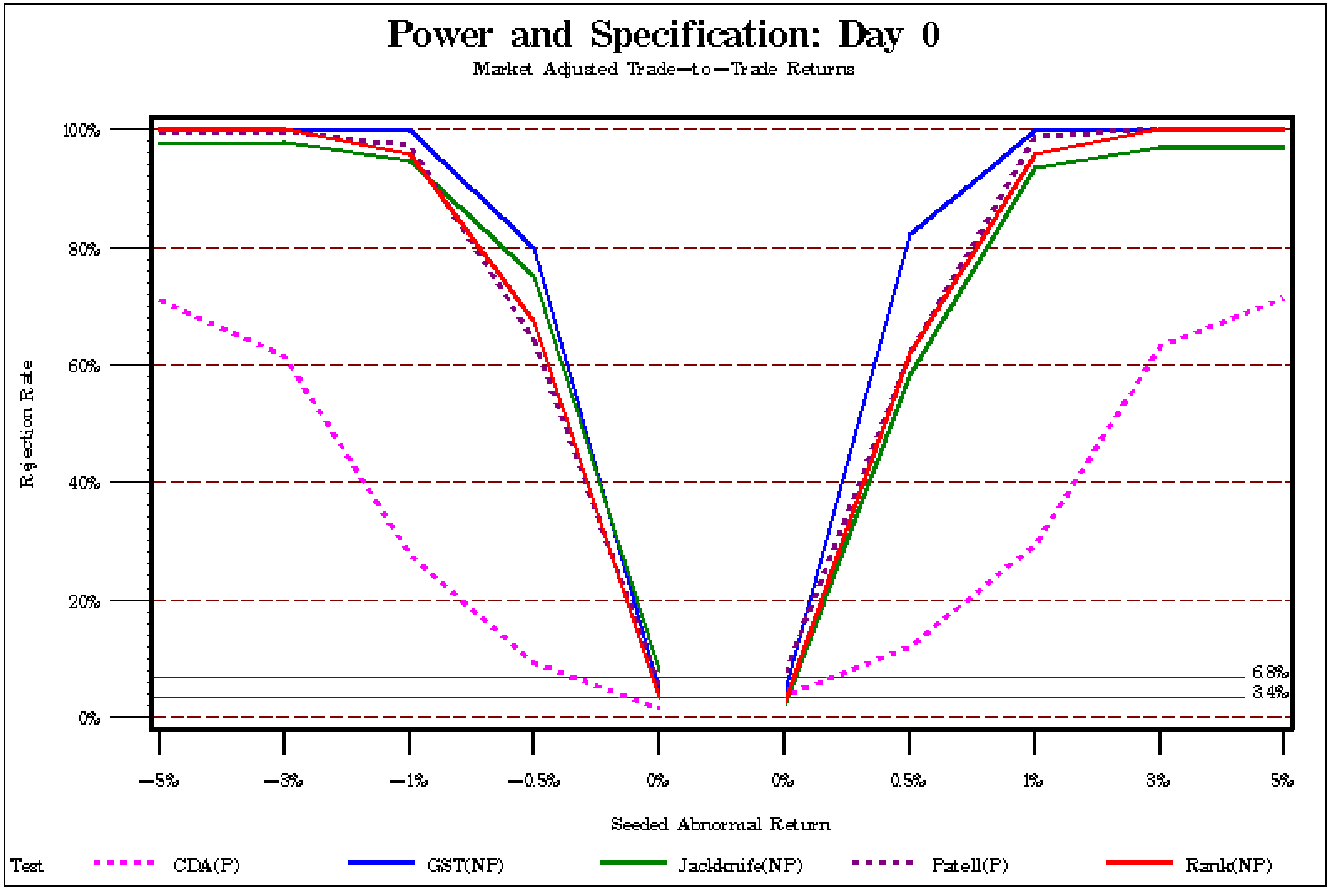

Figure 2

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 model method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

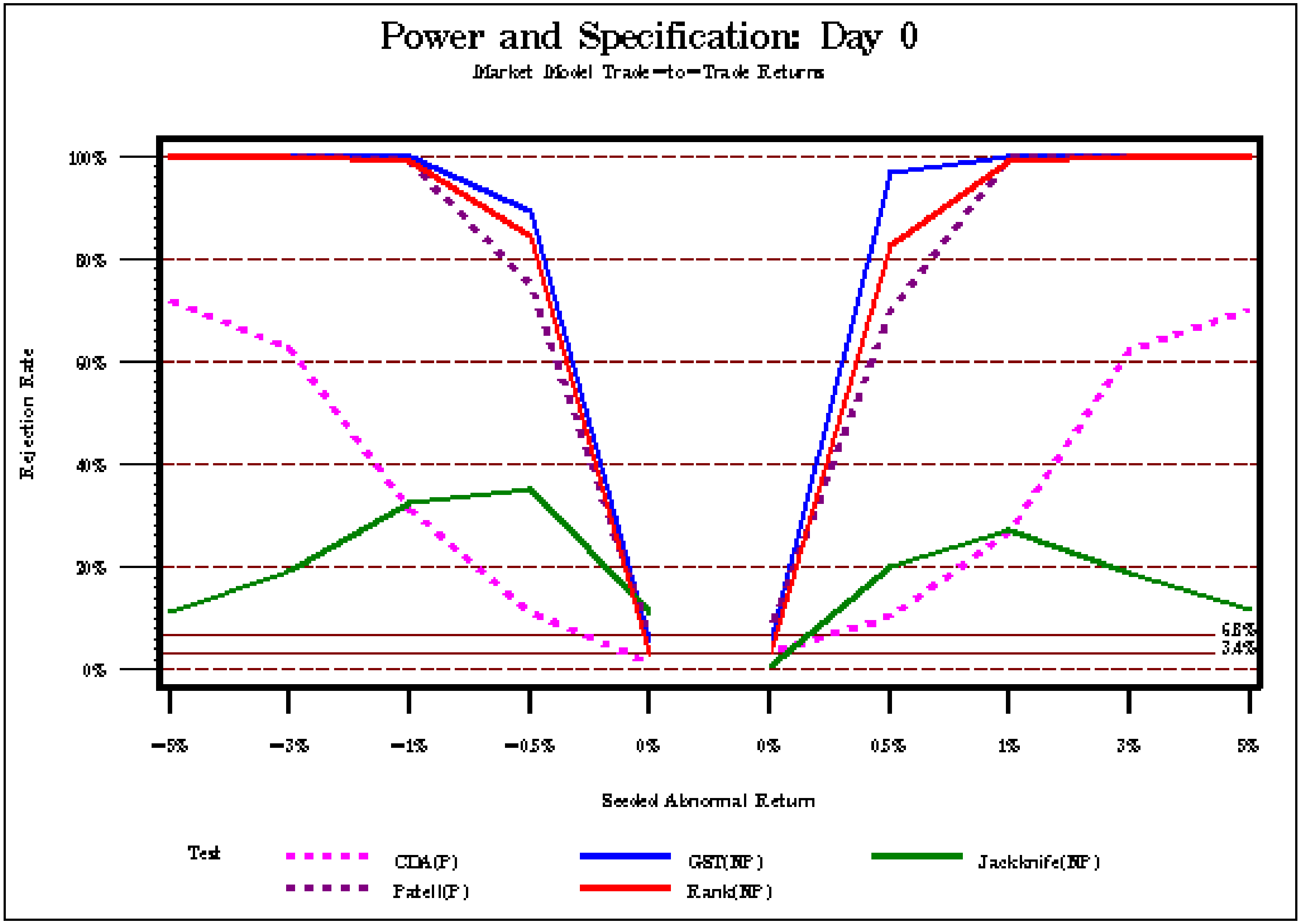

Figure 3

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 lumped returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

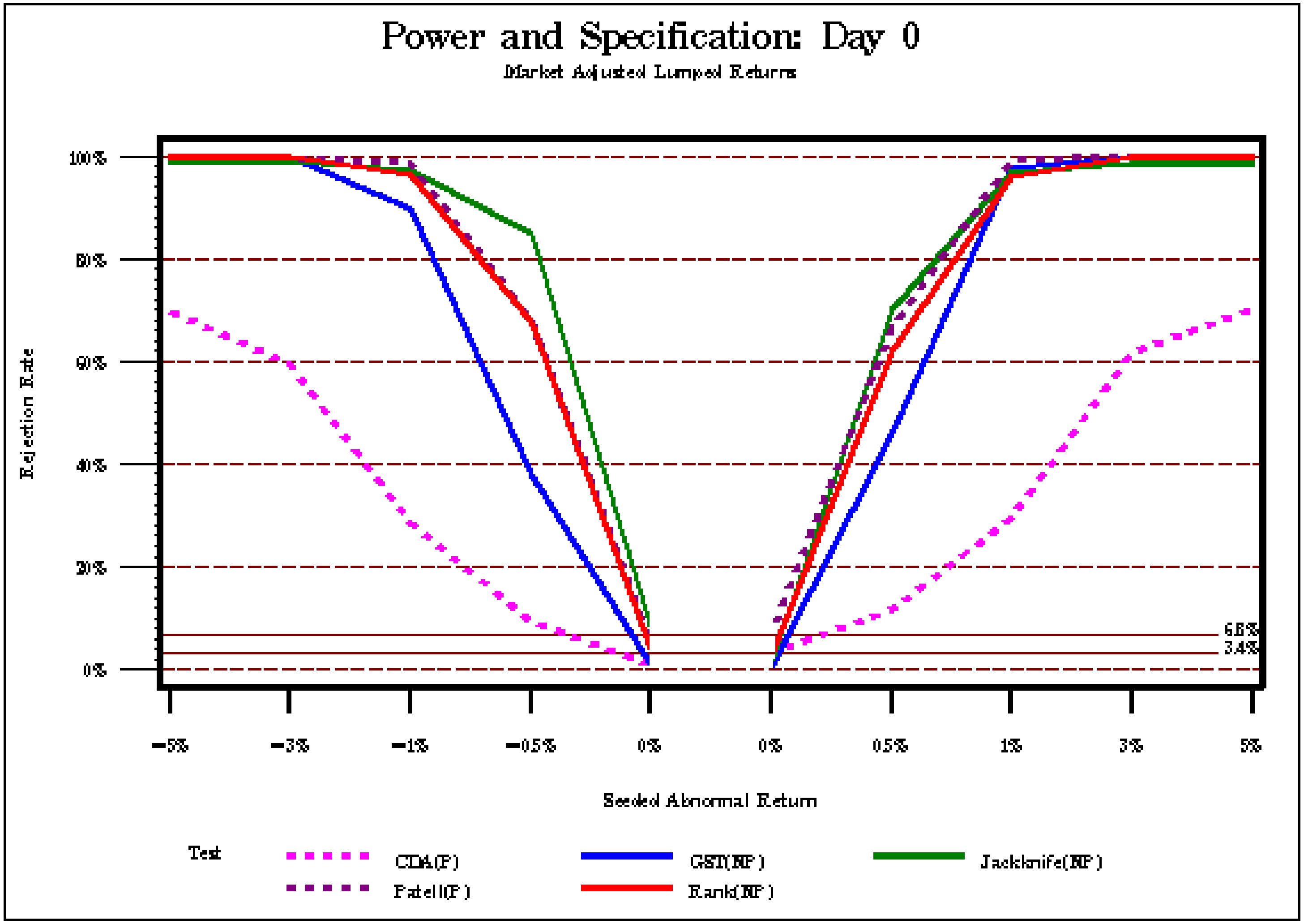

Figure 4

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 model method using lumped returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

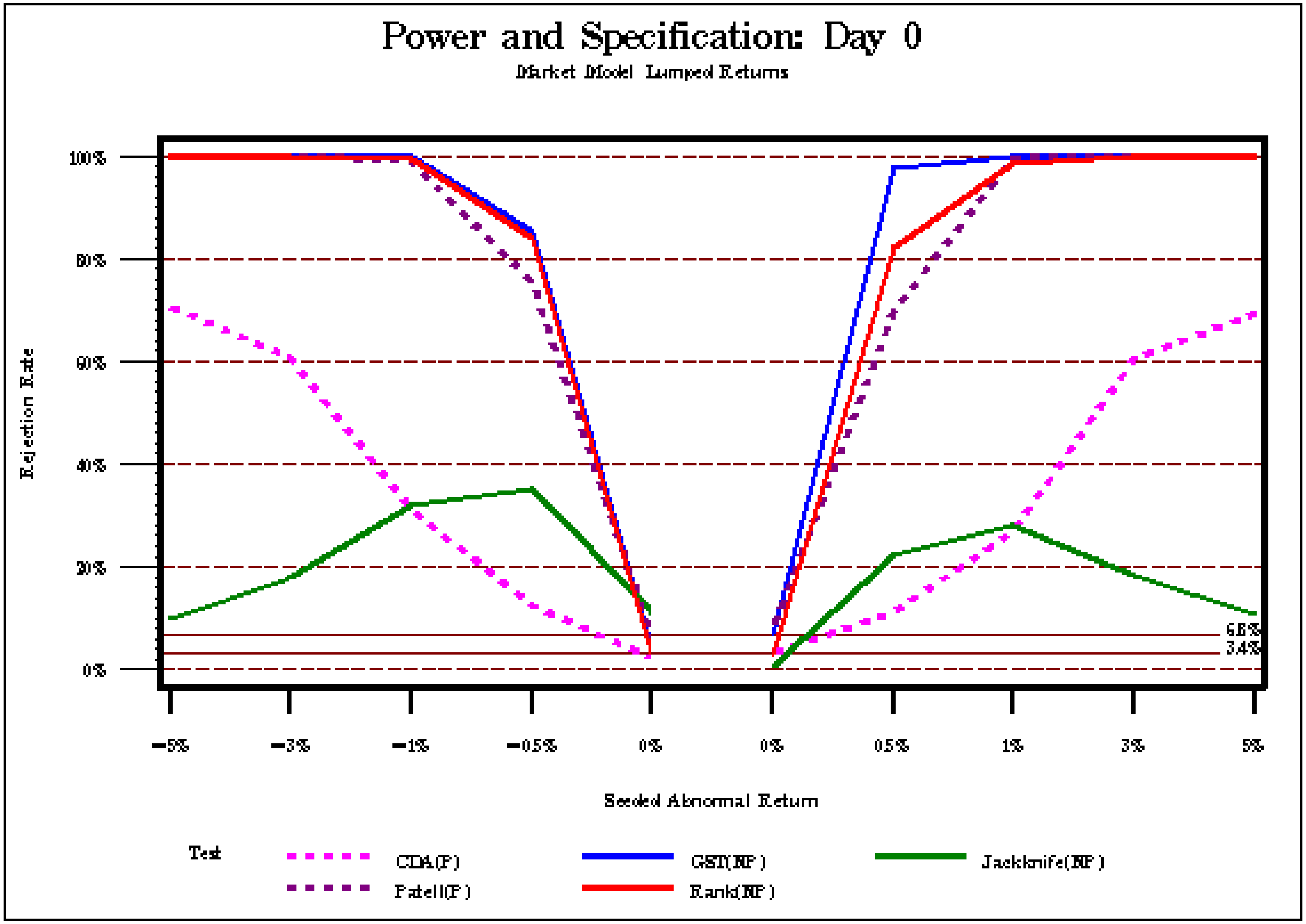

Figure 5

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 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

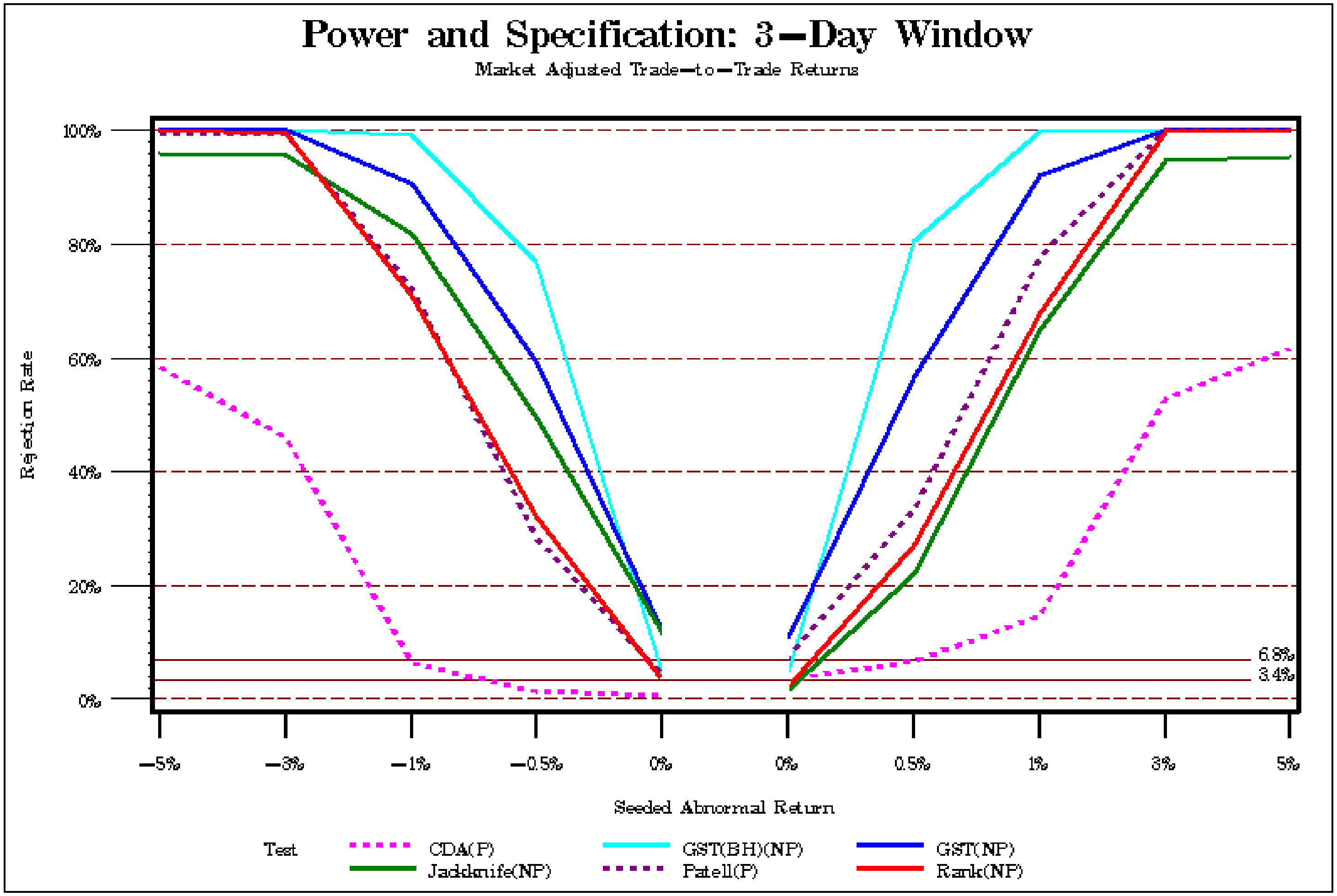

Figure 6

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 model method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

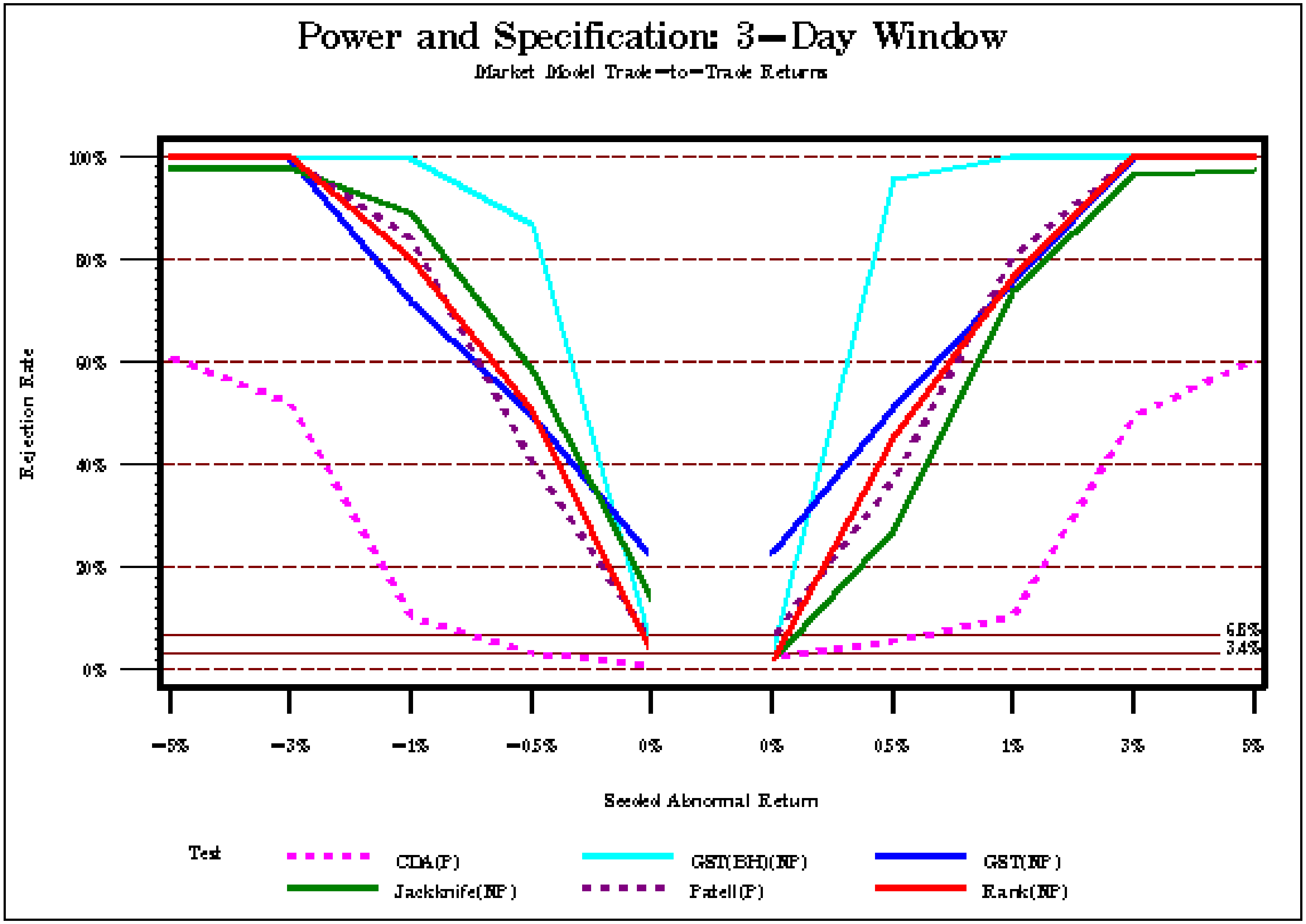

Figure 7

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 lumped returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

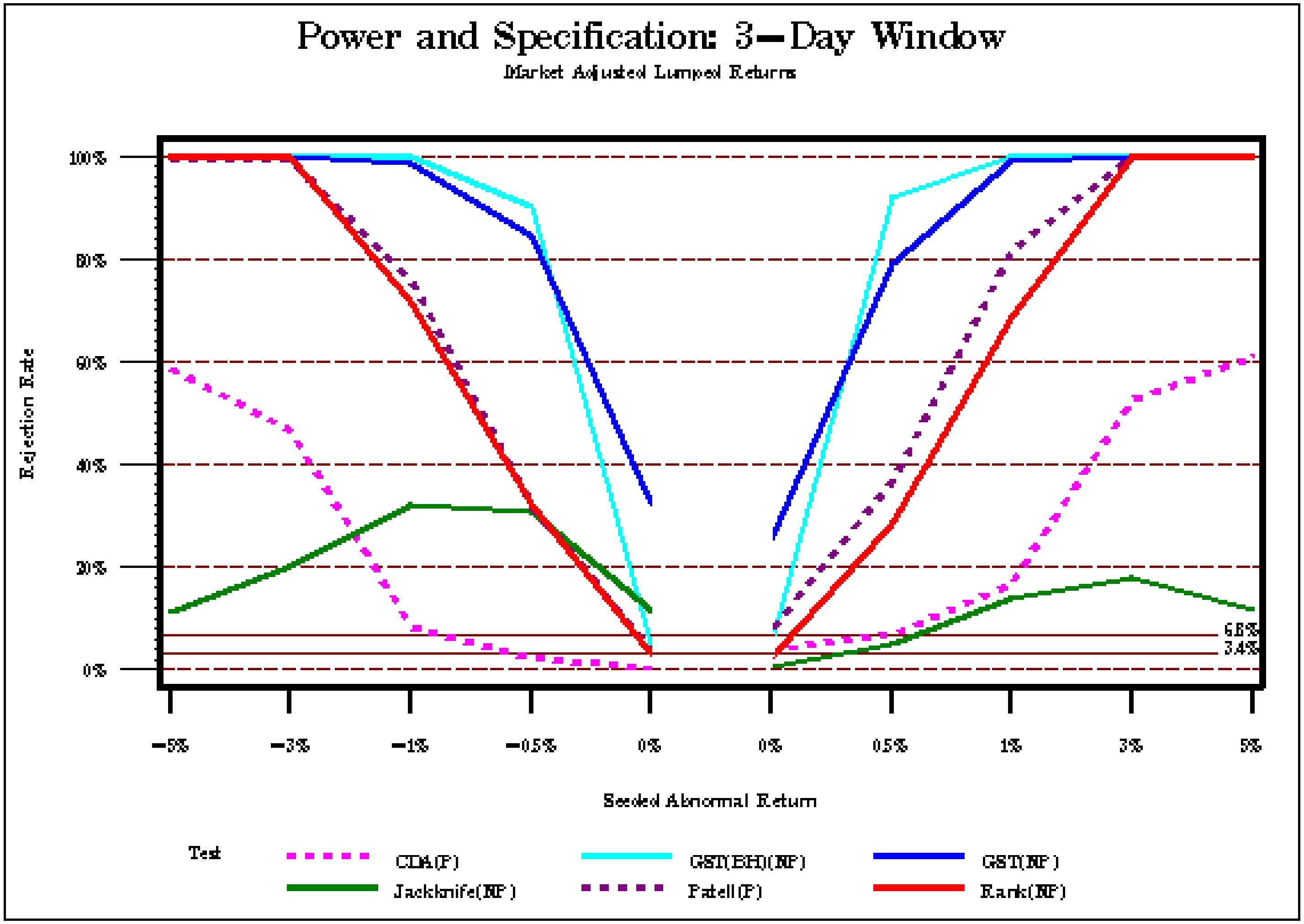

Figure 8

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 model method using lumped returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

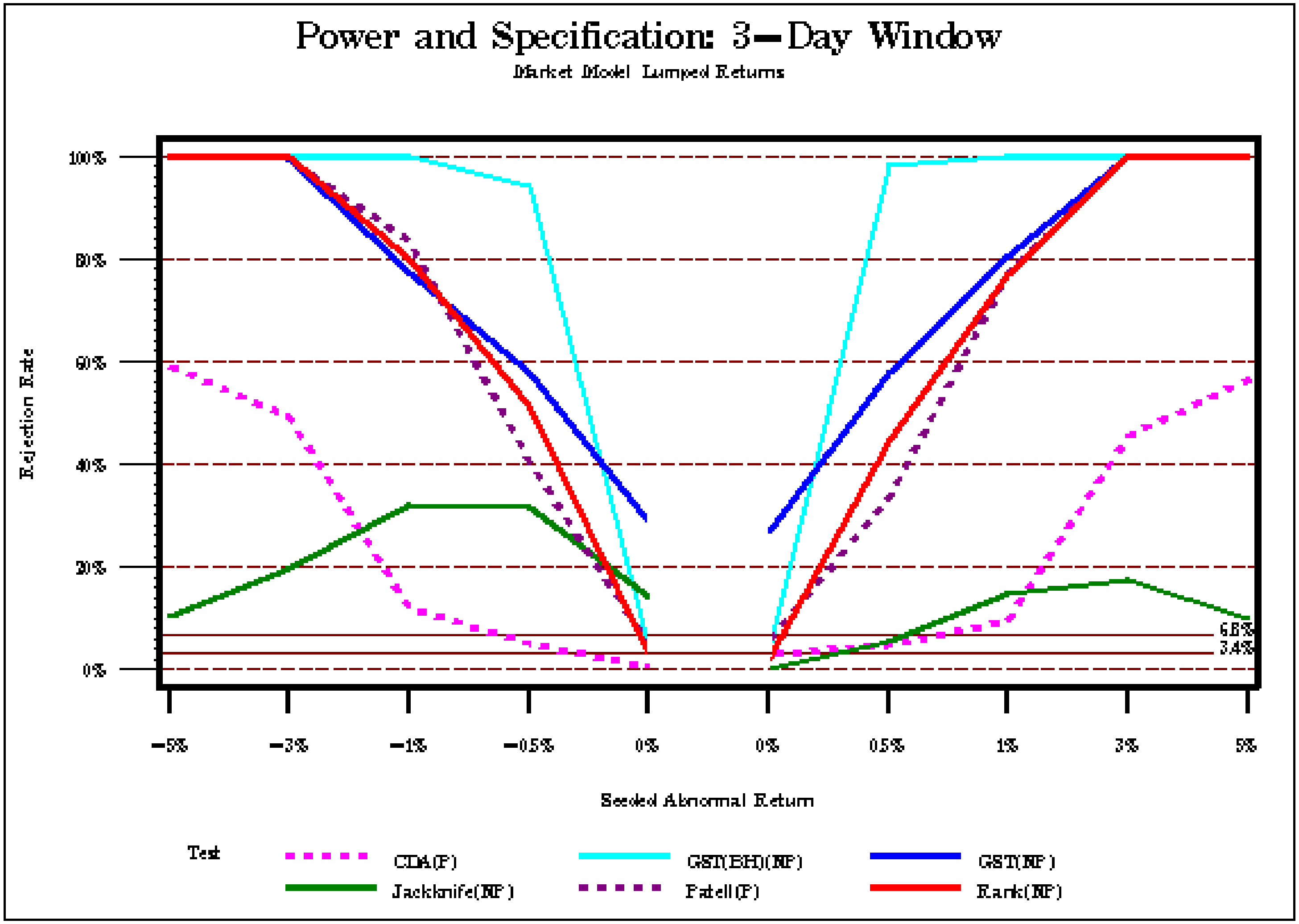

Figure 9

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 a eleven-day window centered on day zero. Abnormal returns are calculated by the market-adjusted method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

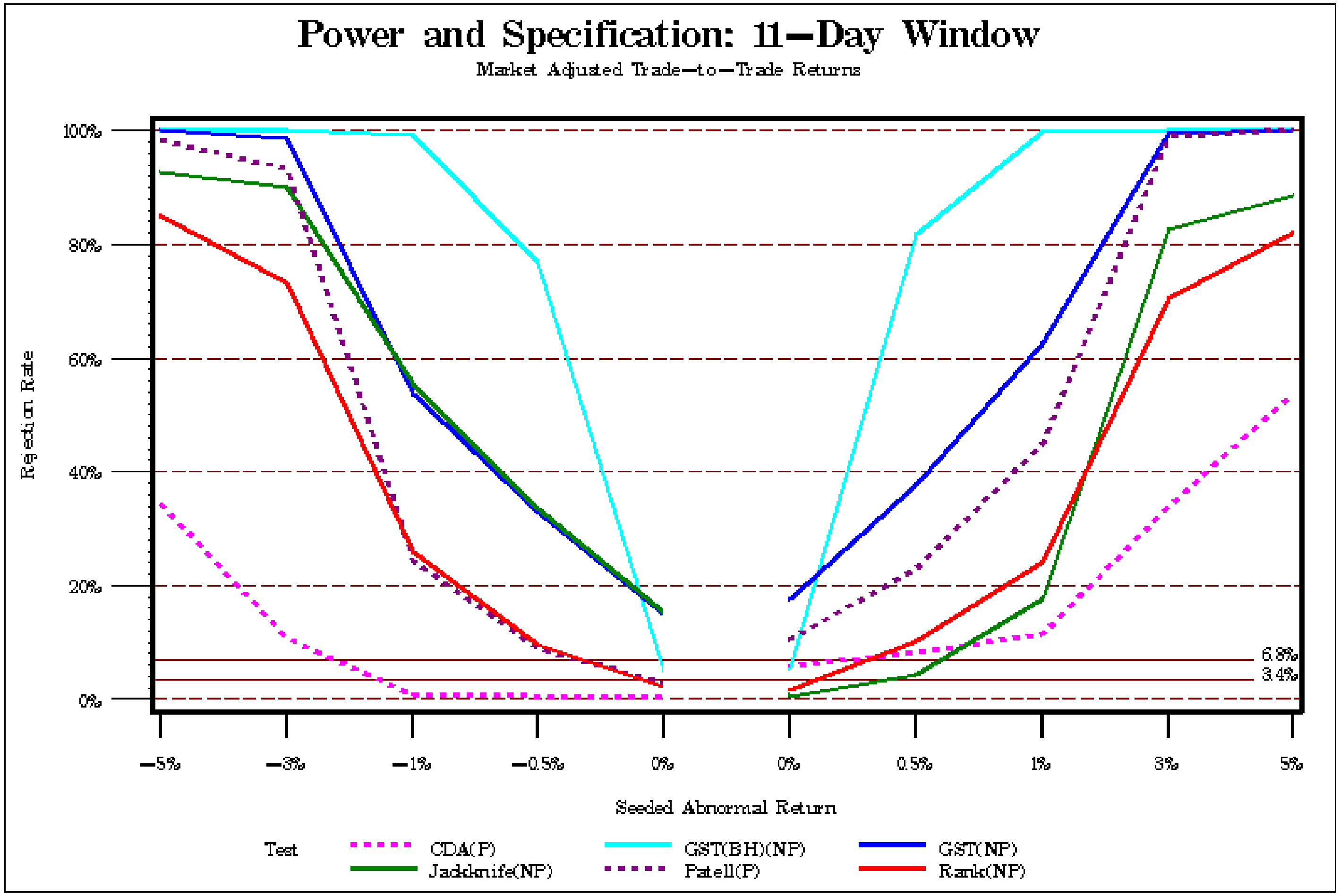

Figure 10

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 a three-day window centered on day zero. Abnormal returns are calculated by the market-adjusted method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

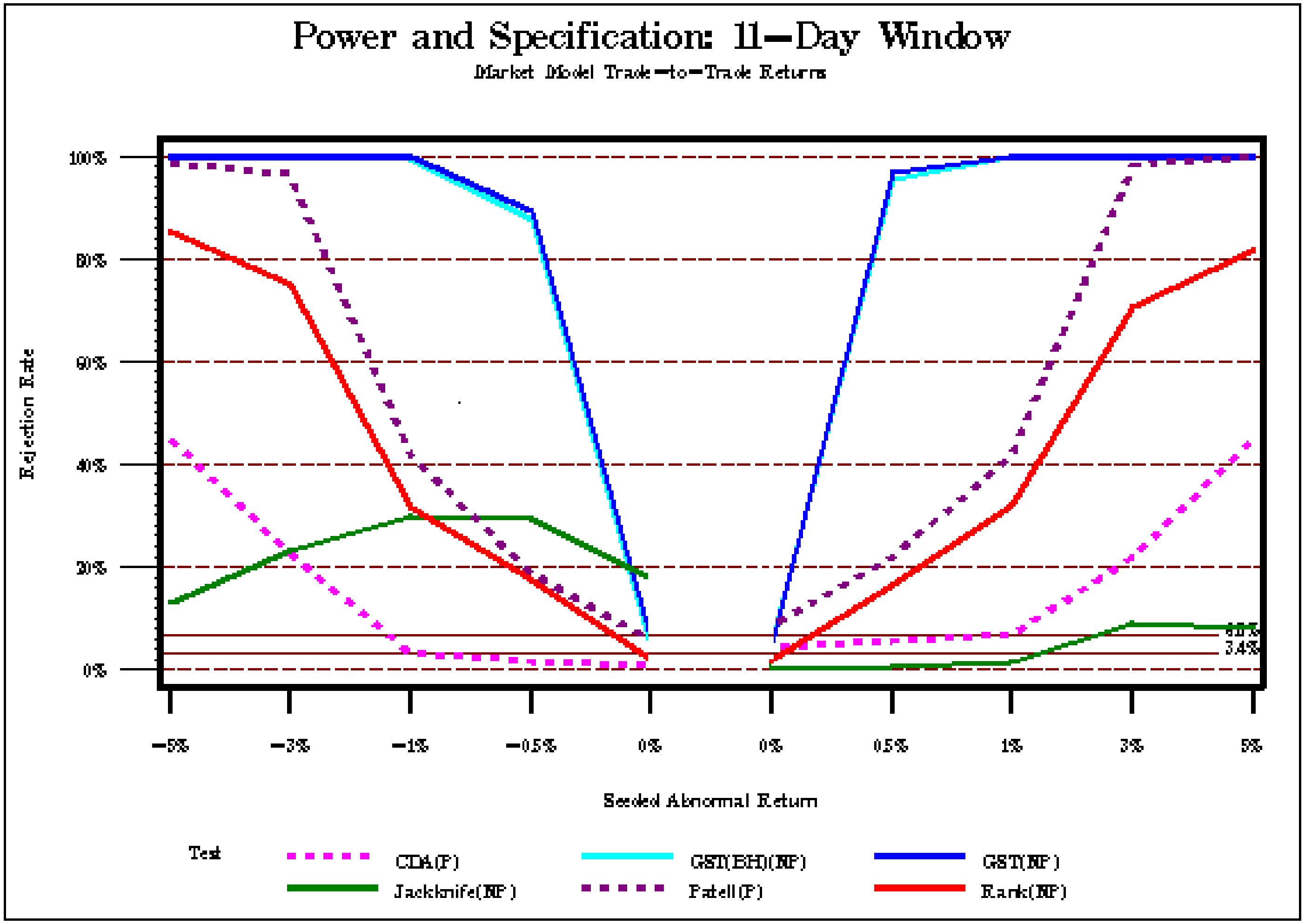

Figure 11

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 a three-day window centered on day zero. Abnormal returns are calculated by the market-adjusted method using lumped returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

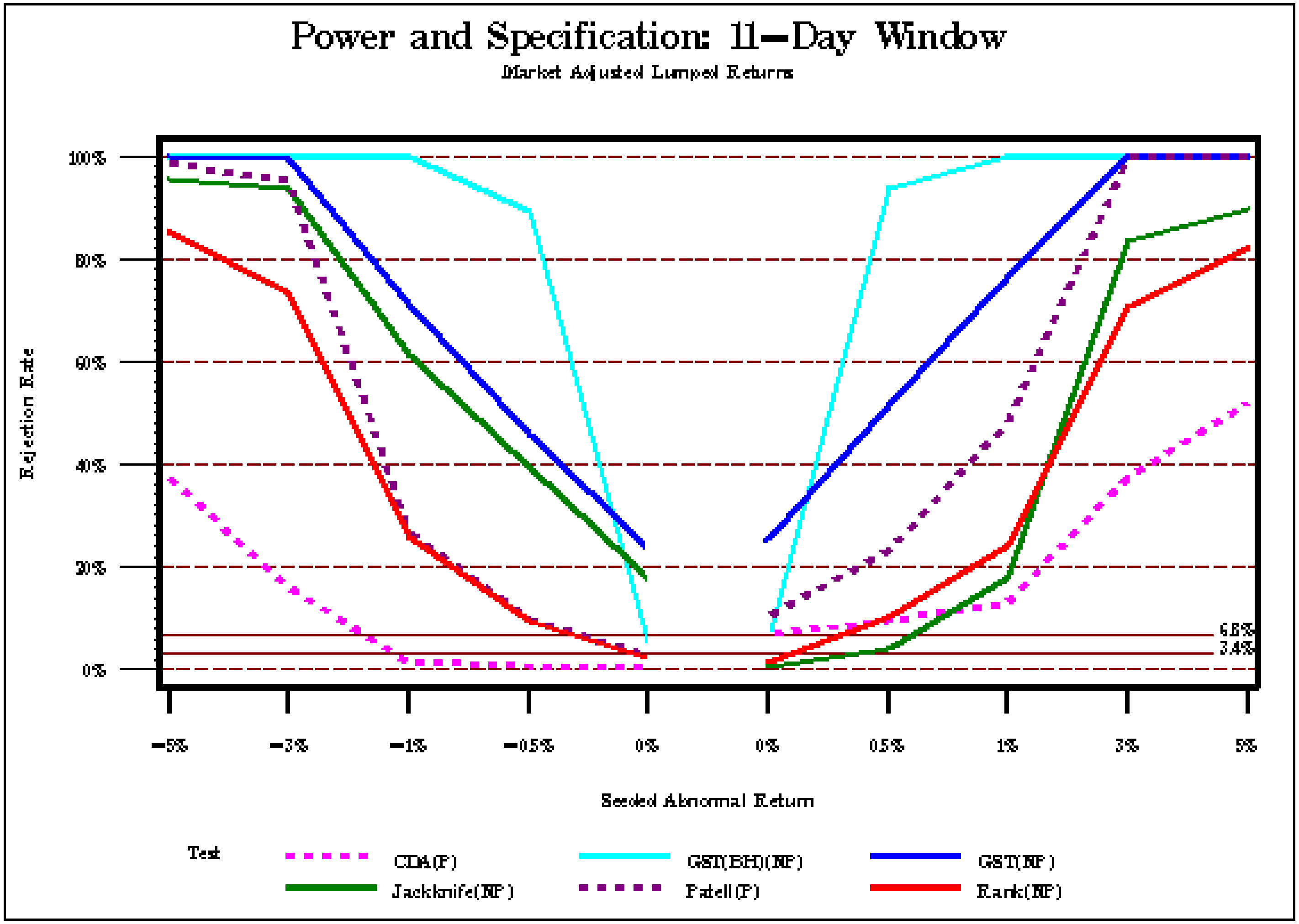

Figure 12

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 a three-day window centered on day zero. Abnormal returns are calculated by the market model method using lumped returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

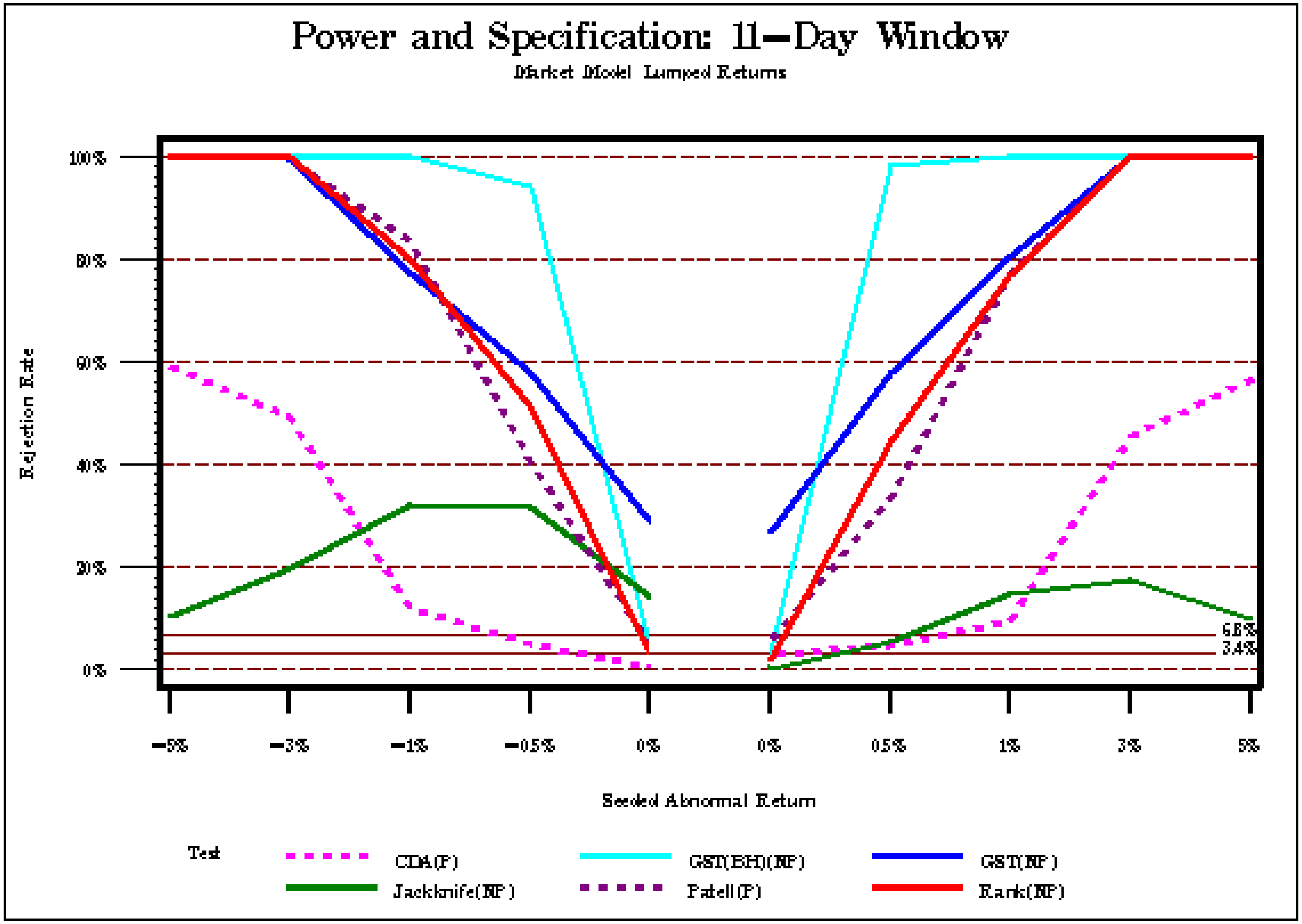

Figure 13

Day zero rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006 with variance increase on the event day

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 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

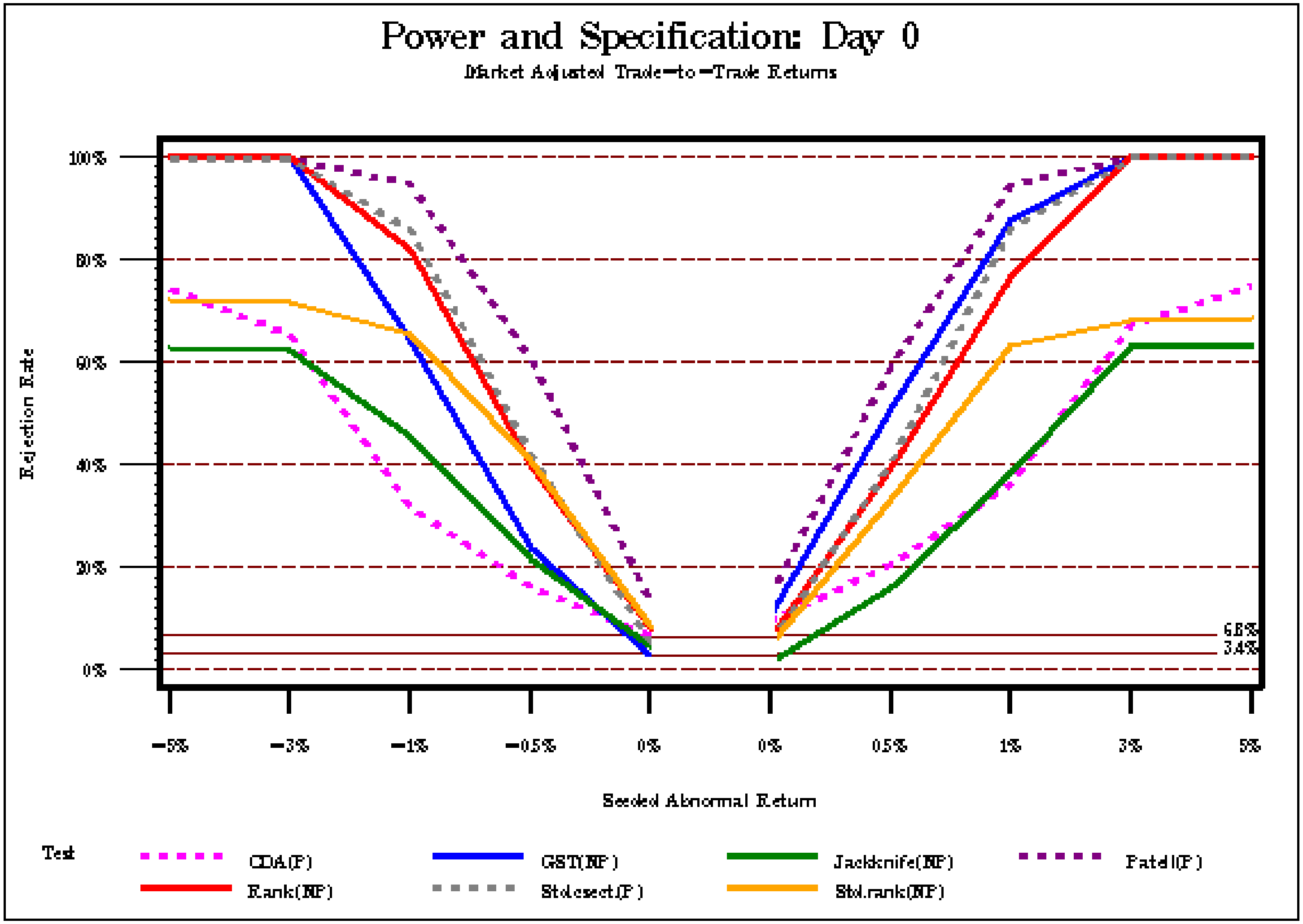

Figure 14

Day zero rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006 with variance increase on the event day

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 model method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

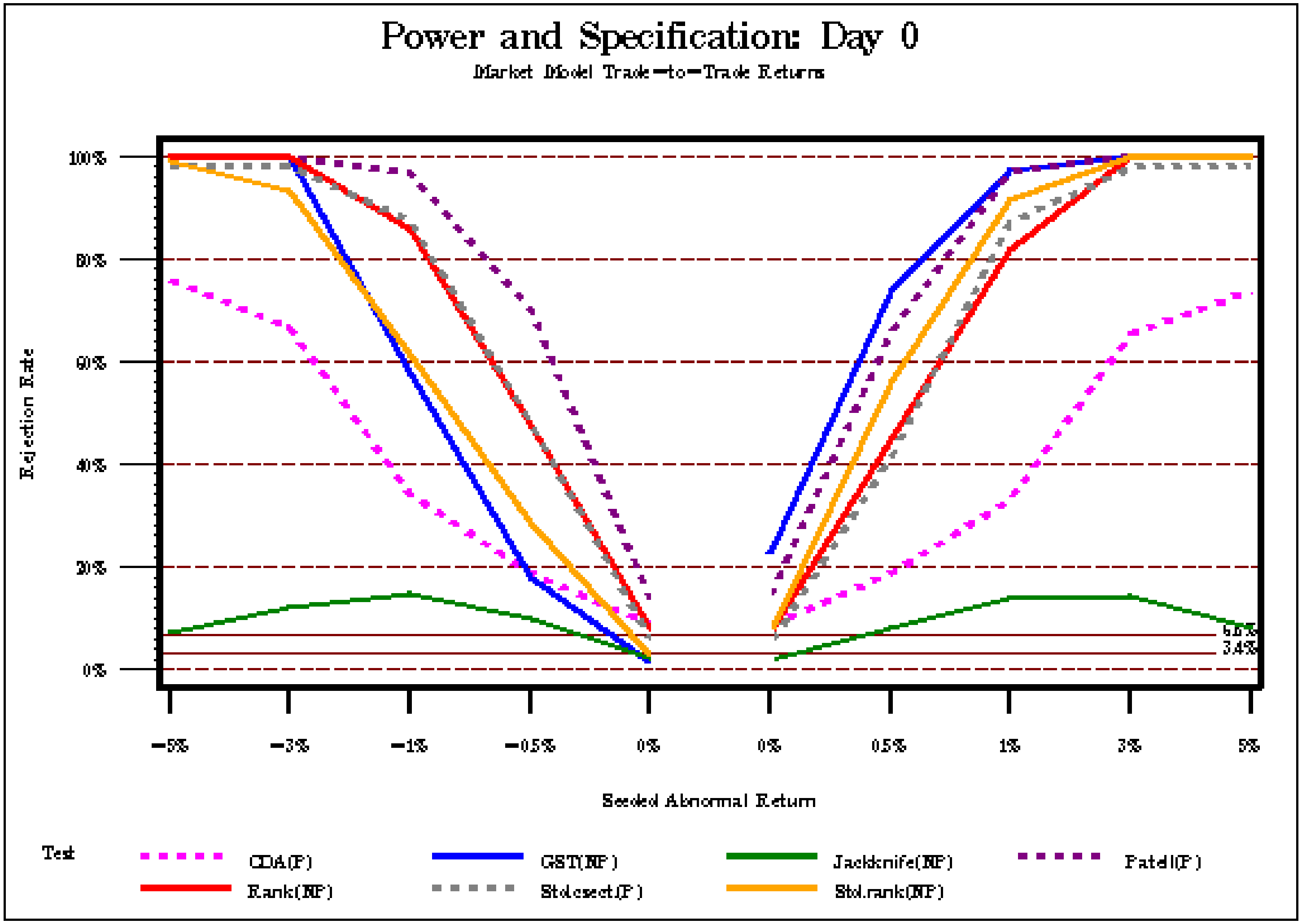

Figure 15

Three-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006 with variance increase on the event day

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 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

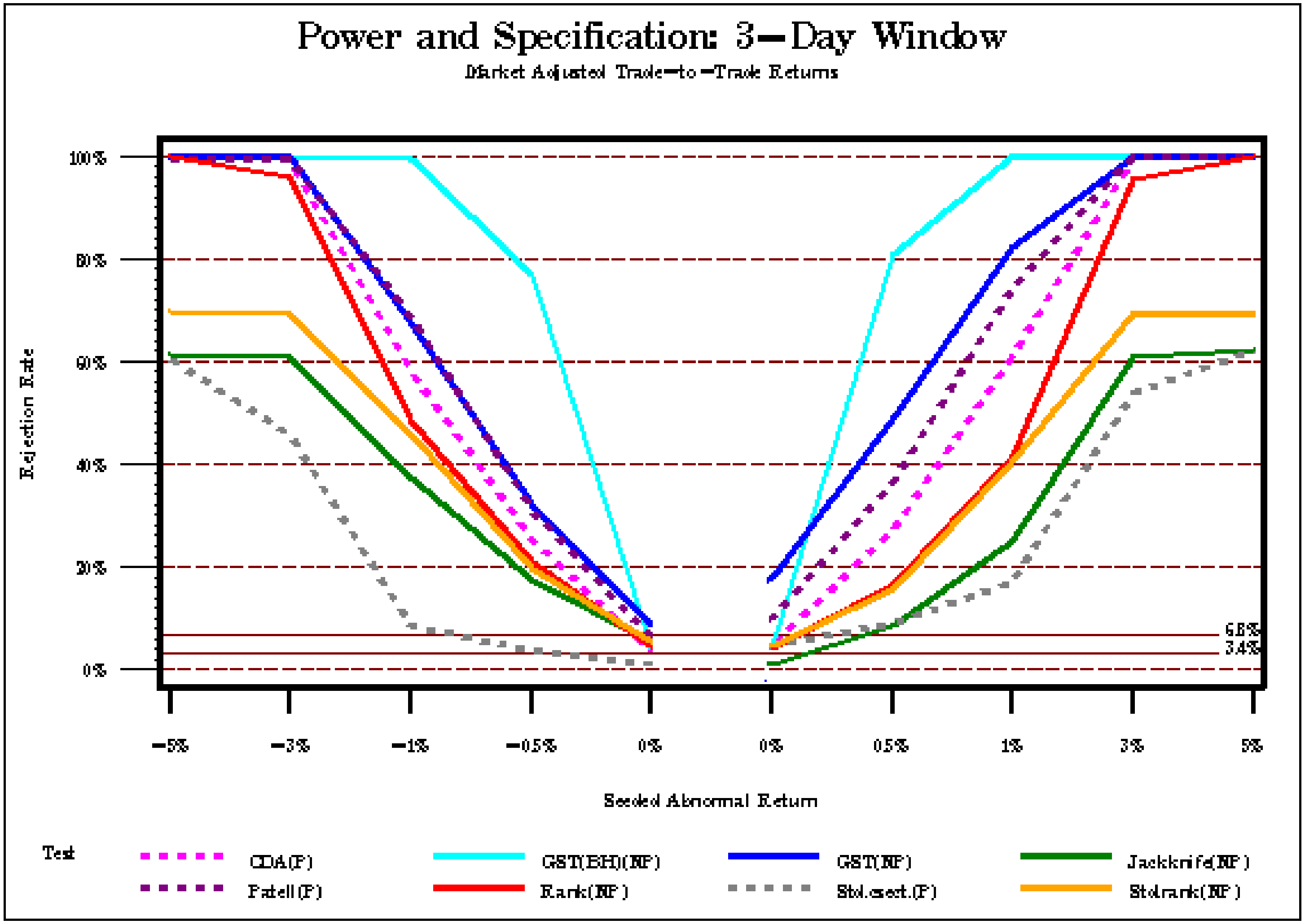

Figure 16

Three-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006 with variance increase on the event day

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 model method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

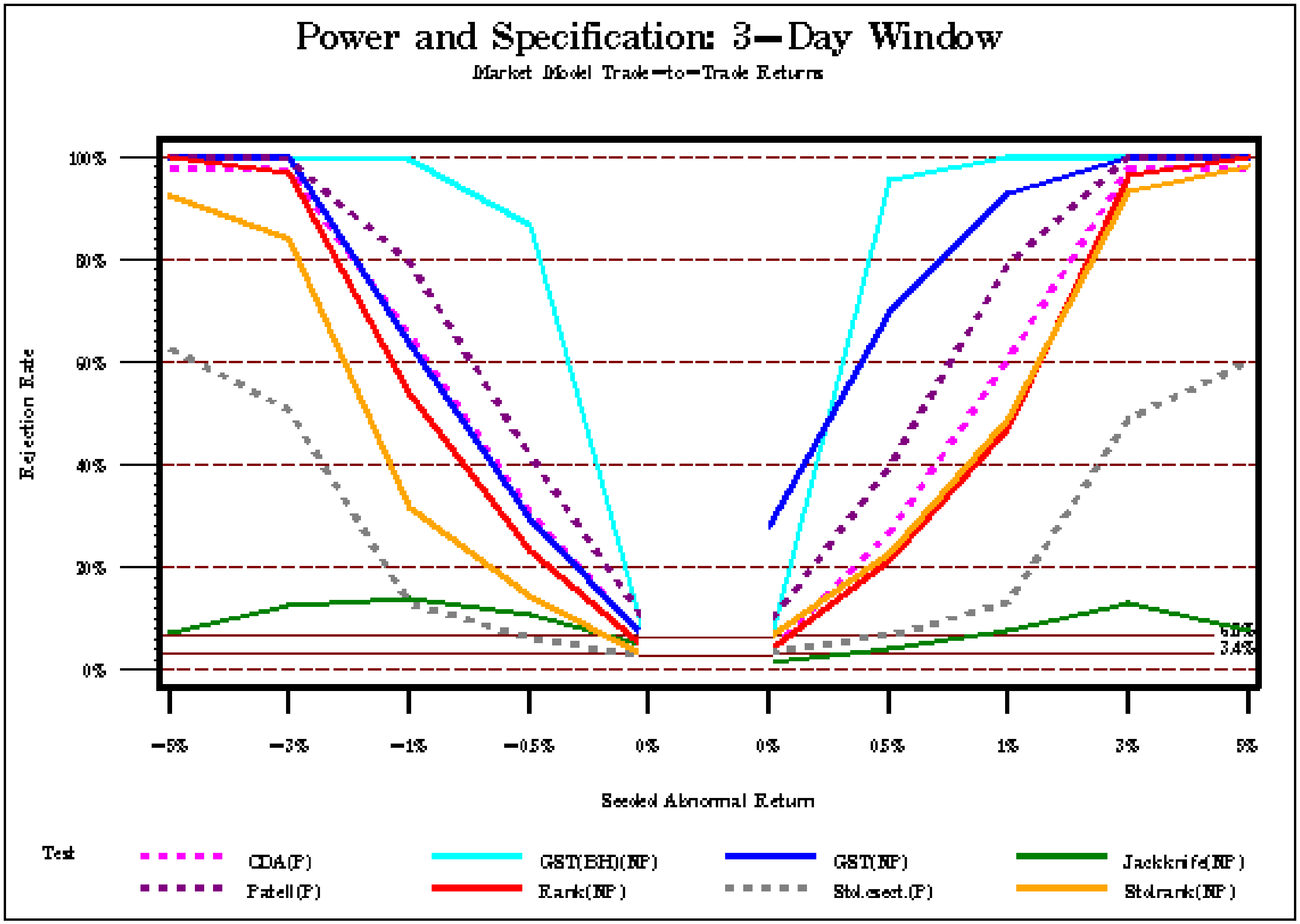

Figure 17

Eleven-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006 with variance increase on the event day

The percentage of 1,000 randomly formed portfolios of 100 securities rejecting the null hypothesis of zero abnormal returns (vertical axis) at different levels of seeded abnormal returns (horizontal axis) based on market adjusted trade-to-trade abnormal return method for an eleven-day window centered on day zero. The 3.4% and 6.8% levels represent the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

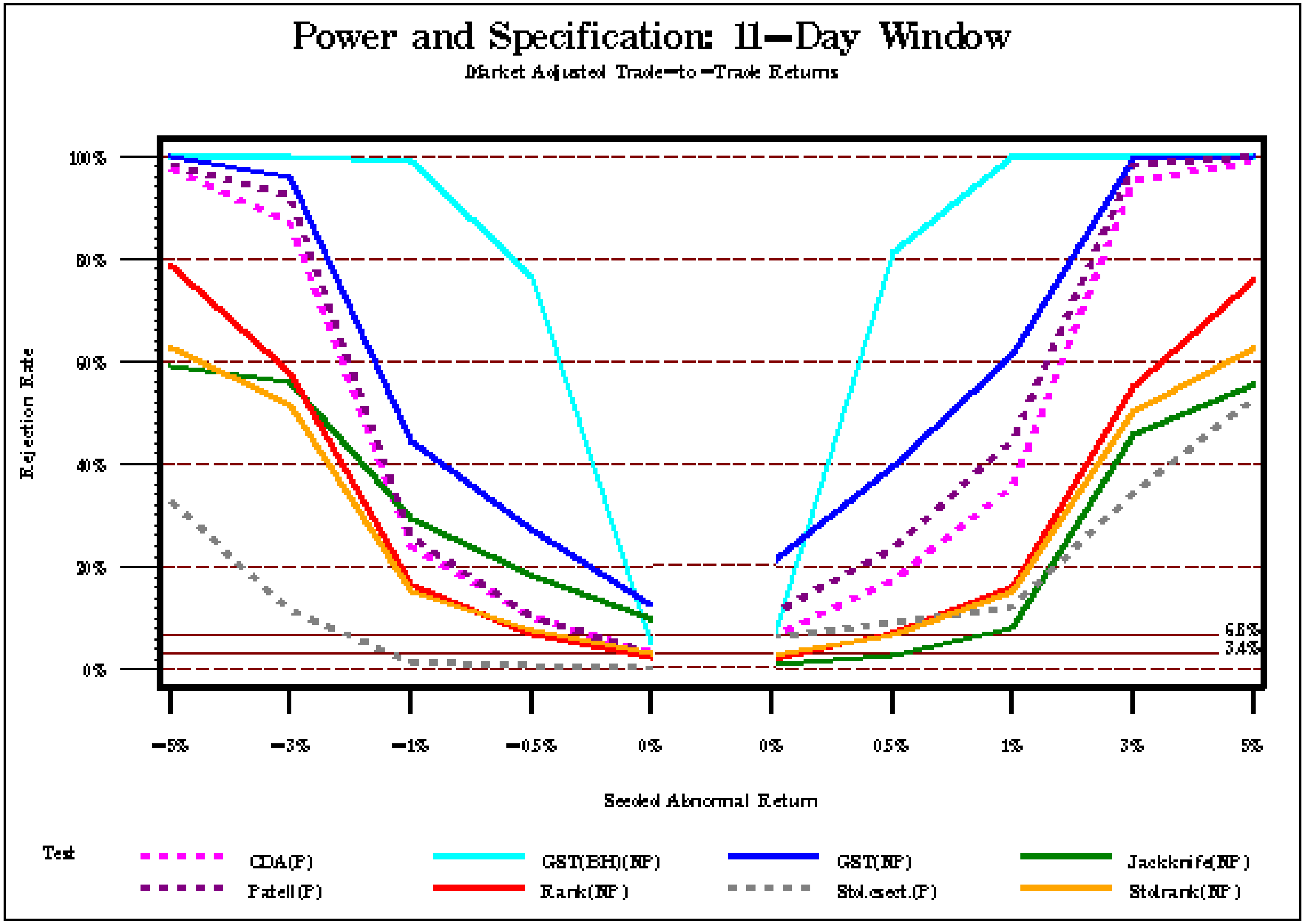

Figure 18

Eleven-day window rejection rates in 1,000 samples of 100 non-U.S. stocks each, 1988-2006 with variance increase on the event day

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 model method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

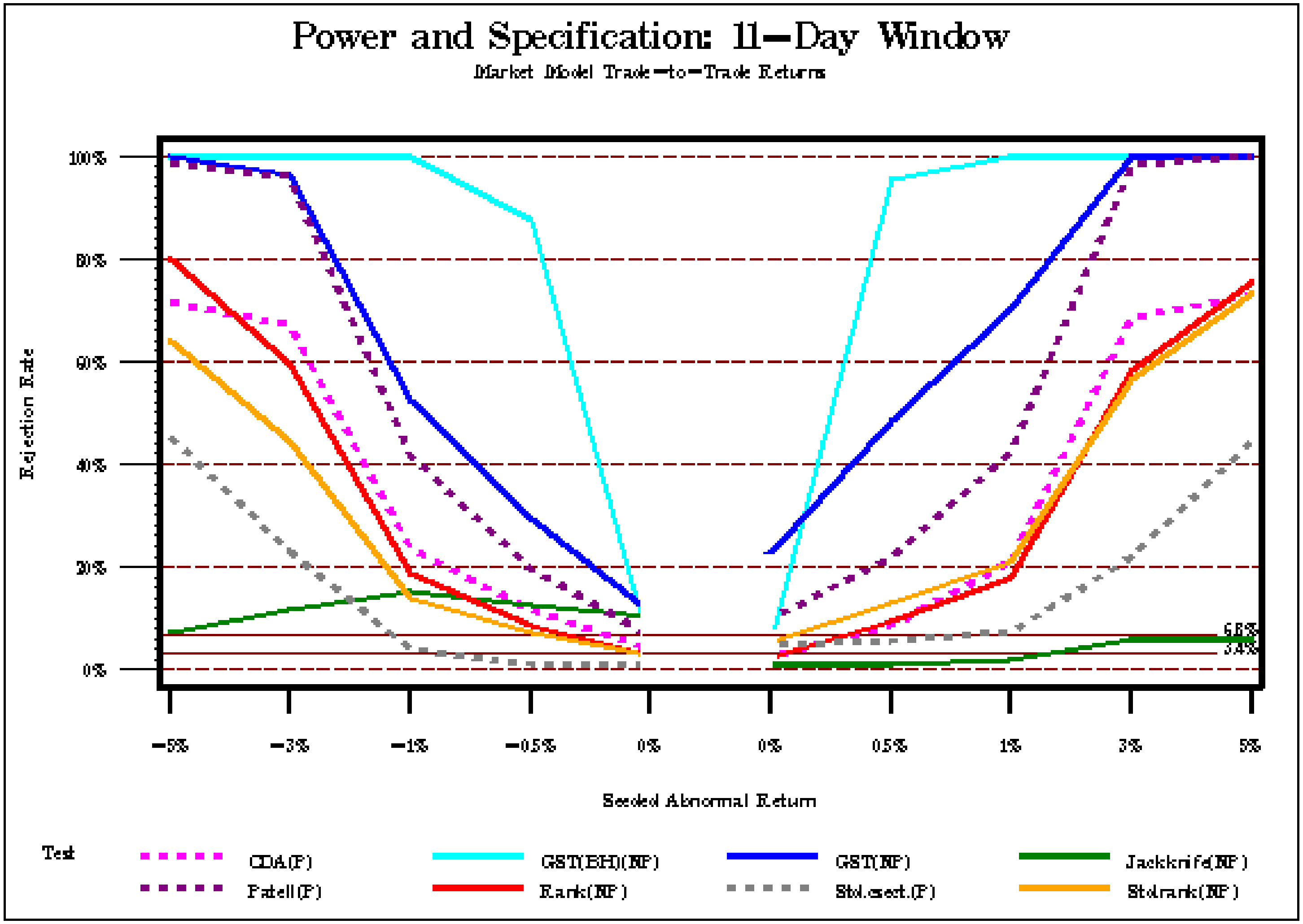

Figure 19

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

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 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

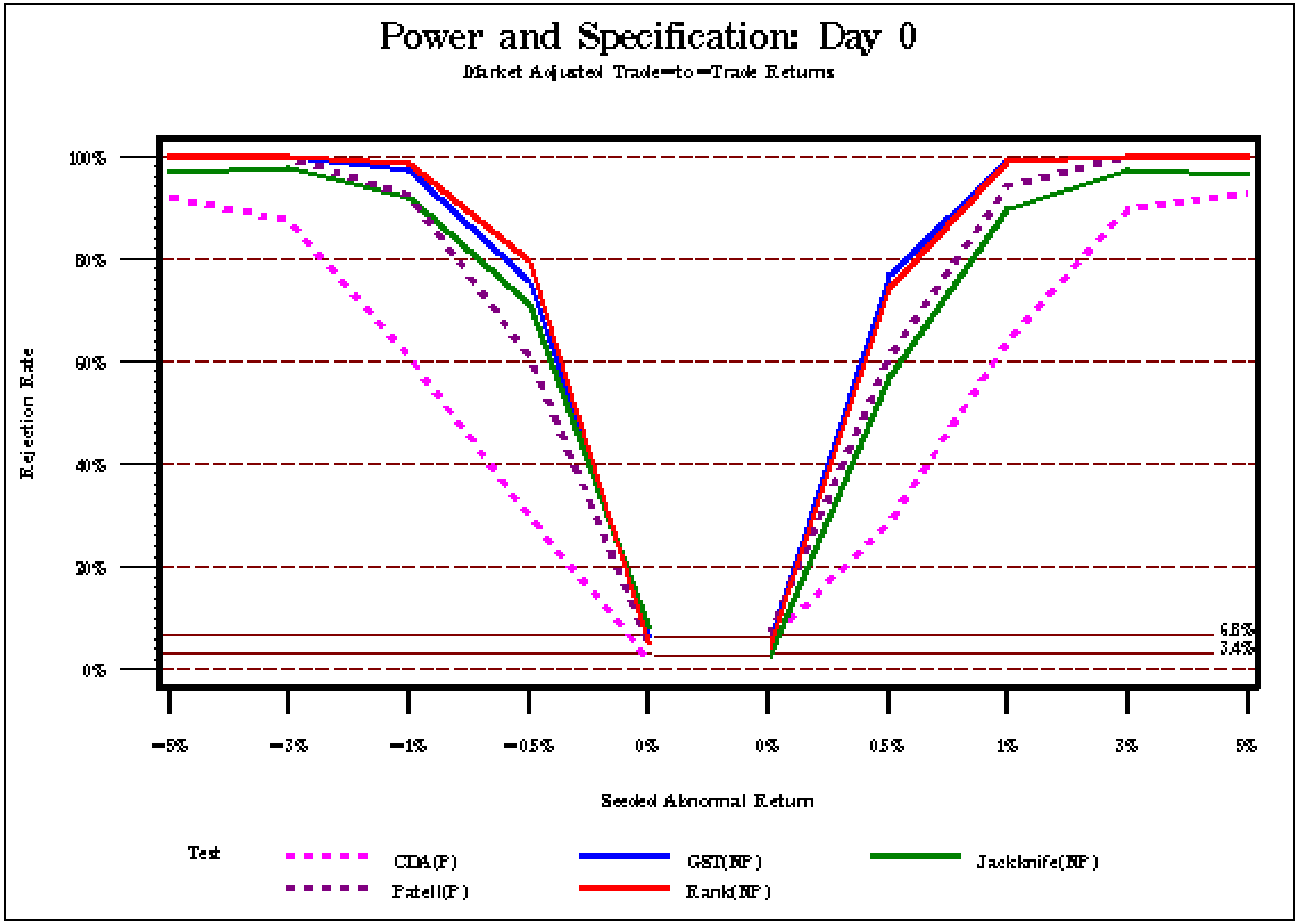

Figure 20

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

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 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

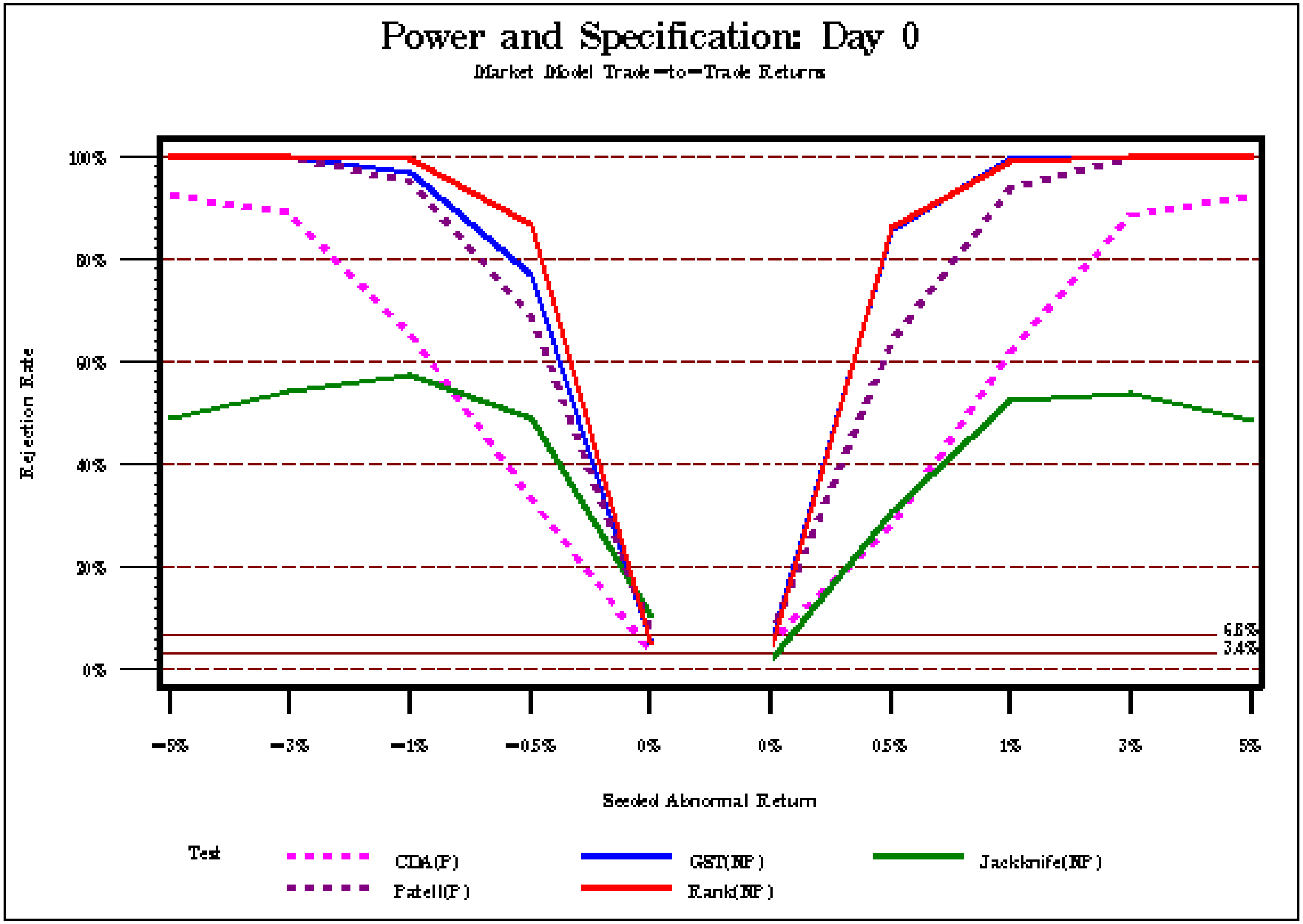

Figure 21

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

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 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

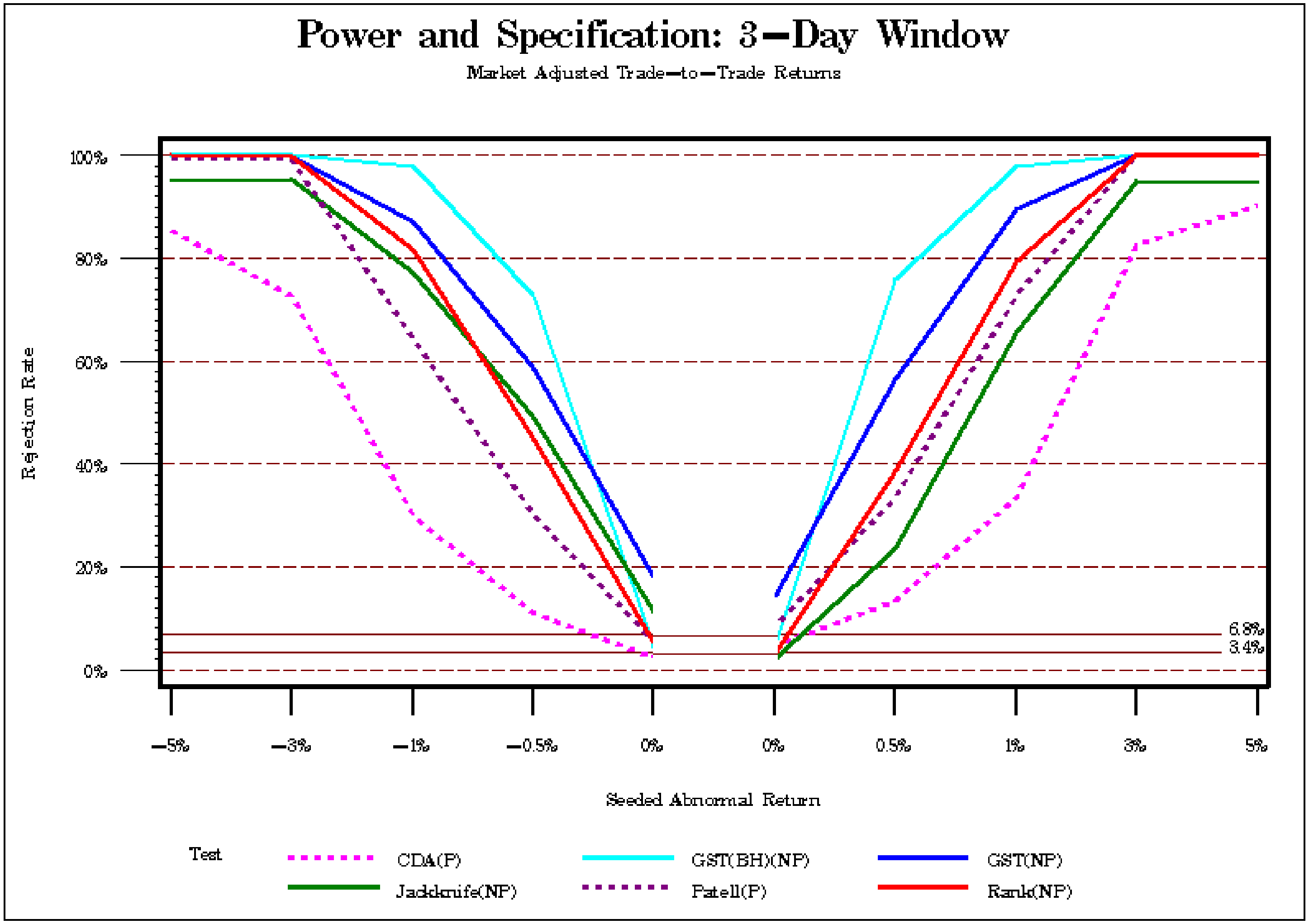

Figure 22

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

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 model method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

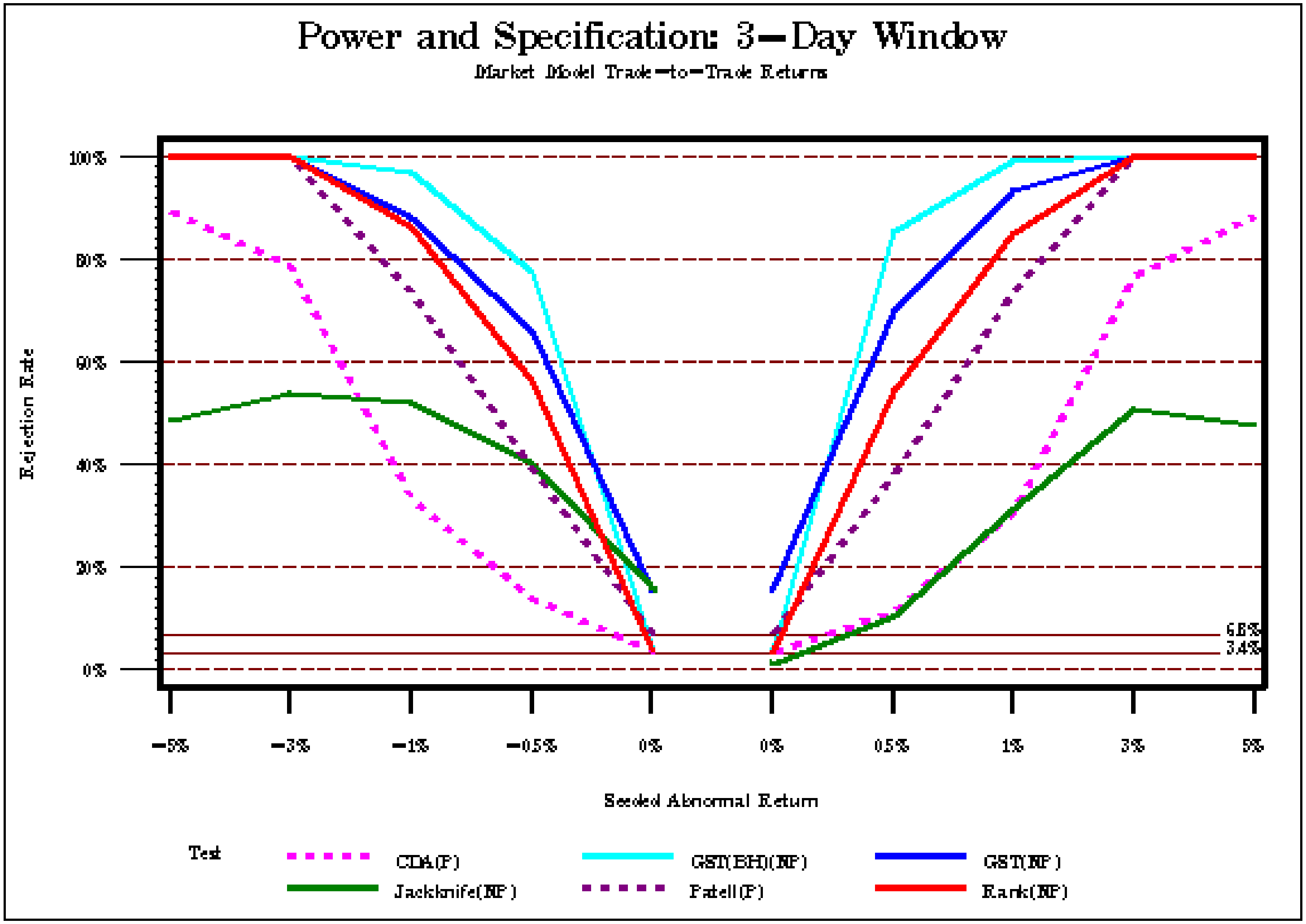

Figure 23

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

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 eleven-day window centered on day zero. Abnormal returns are calculated by the market-adjusted method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.

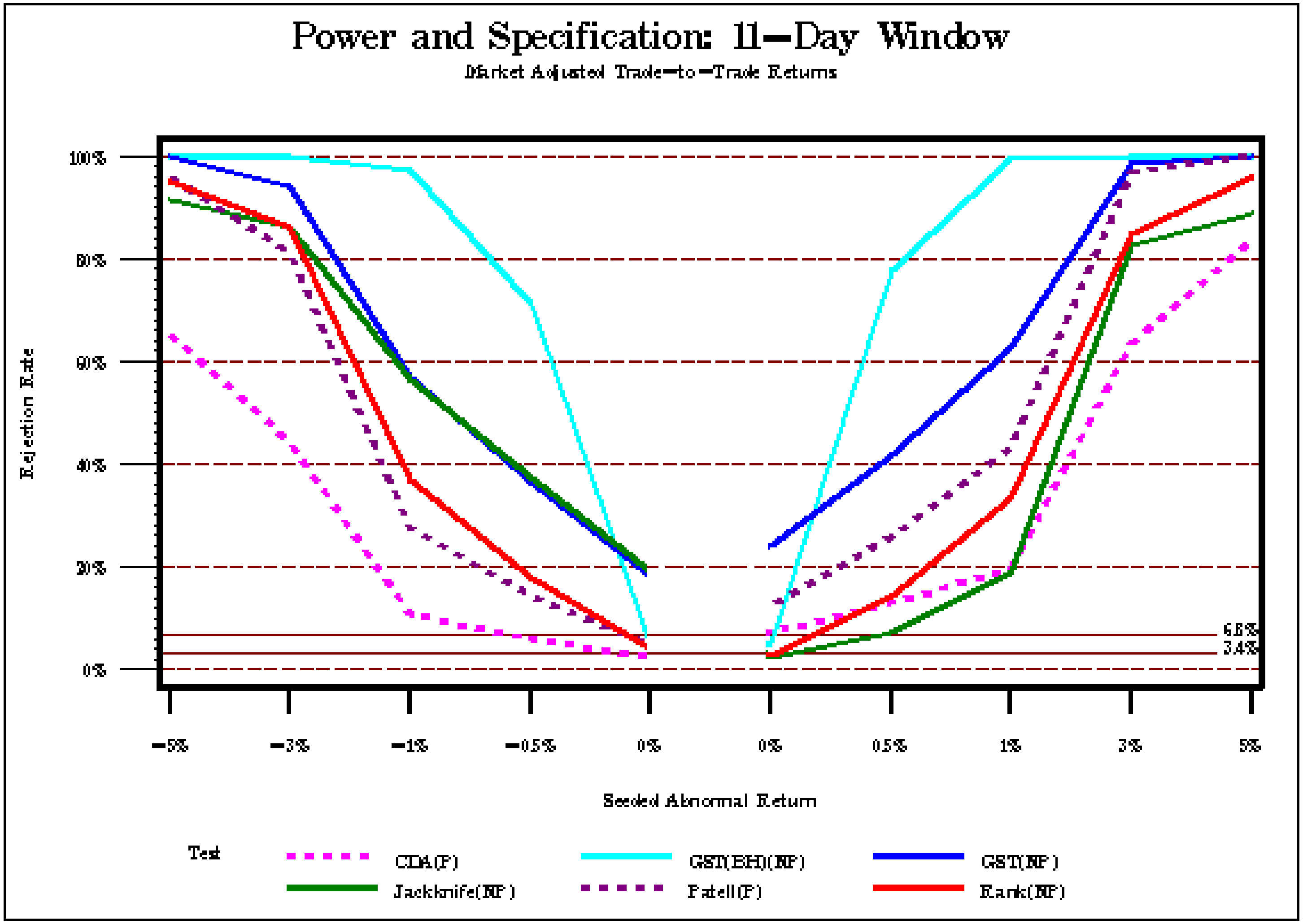

Figure 24

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

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 eleven-day window centered on day zero. Abnormal returns are calculated by the market model method using trade-to-trade returns. The 3.4% and 6.8% rejection rates are the 99% confidence limits for the normal approximation to 1,000 binomial trials with a 5% probability of success (rejection) on each trial.