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Measuring Abnormal Daily Trading Volume for Samples of NYSE/ASE and NASDAQ Securities Using Parametric and Nonparametric Test Statistics

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Abstract. We extend prior research on the empirical properties of daily trading volume and methods to detect abnormal trading volume in two ways. We compare the performance of a nonparametric test statistic with the parametric test statistic used in prior research and we study samples of NASDAQ securities as well as samples of NYSE/ASE securities. Prior research has focused exclusively on NYSE securities. We find the nonparametric test statistic is more powerful in detecting abnormal trading volume than the parametric test statistic in both samples of NYSE/ASE and NASDAQ securities. We also document that abnormal trading volume will be detected more often in samples of NYSE/ASE securities compared to NASDAQ securities.

Key words: parametric/nonparametric test statistics, daily trading volume, abnormal trading volume, event studies

1. Introduction

We study the empirical properties of daily trading volume and alternative methods to detect abnormal trading volume. Compared to the distributional properties of security returns and alternative methods to measure abnormal security price performance (e.g., Brown and Warner (1985), Jain (1986), Corrado (1989), and Campbell and Wasley (1993)), much less evidence has been provided on the distributional properties of daily trading volume and the power of alternative test statistics to detect abnormal trading volume. Given recent theoretical research modeling the trading volume reaction to information events (e.g., Holthausen and Verrecchia (1990), Kim and Verrecchia (1991a, 1991b, 1994), and Demski and Feltham (1994)), evidence of the characteristics of daily trading volume and the ability of alternative test statistics to detect abnormal trading volume will aid researchers in designing empirical tests of these models.

Two prior studies of daily trading volume include Ajinkya and Jain (1989) and Cready and Ramanan (1991). Ajinkya and Jain (1989) document that raw trading volume for NYSE securities is highly nonnormal, but that a log-transformation yields trading volume measures that are approximately normally distributed. Ajinkya and Jain's (1989) analysis leads them to conclude that "in general, the use of daily trading volume data in event studies is straightforward." Cready and Ramanan (1991) assess the sensitivity of Ajinkya and Jain's (1989) results to the method used to induce (i.e., simulate) abnormal trading volume. Cready and Ramanan (1991) contrast a multiplicative approach to induce abnormal trading volume with the additive approach used by Ajinkya and Jain (1989). They find the rejection rates reported by Ajinkya and Jain (1989) overstate the power of the test to detect abnormal trading volume. Cready and Ramanan (1991) document that in a sample of 50 NYSE securities, a 20% volume increase will be detected slightly more than 40% of the time, compared to a detection rate of more than 90% reported by Ajinkya and Jain (1989). The credibility of Cready and Ramanan's (1991) results is enhanced by the finding that the rejection percentages for abnormal volume at the time of actual earnings announcement dates are more consistent with their simulation-based rejection rates when compared to the simulation-based rejection rates reported by Ajinkya and Jain (1989).

As the initial articles addressing the distributional characteristics of trading volume and the detection of abnormal trading volume, the Ajinkya and Jain (1989) and Cready and Ramanan (1991) studies provide important insights into the use of trading volume measures in event study settings. Two features common to both studies are that simulations were based exclusively on samples of NYSE securities and that only one (and the same) parametric test statistic's ability to detect abnormal trading volume was evaluated. Two issues left unanswered are whether their findings are representative of the distributional characteristics of the trading volume of non-NYSE securities such as the large population of firms traded on the NASDAQ system, and whether alternative test statistics exhibit greater power to detect abnormal trading volume when compared to the parametric test statistic examined by both Ajinkya and Jain (1989) and Cready and Ramanan (1991).

In this study we extend prior research by addressing the two questions posed above. We provide evidence on the empirical properties of daily trading volume and abnormal trading volume for samples of NASDAQ securities and compare these properties with those of NYSE/ASE securities. The study of NASDAQ securities is an important issue because the NASDAQ system, and the securities trading on it, differ in many respects from the NYSE. Accordingly, there are reasons to expect the results reported in Ajinkya and Jain (1989) and Cready and Ramanan (1991) for NYSE securities not to be generalized to NASDAQ securities. Campbell and Wasley (1993) report that random samples of NASDAQ securities exhibit three times the number of zero returns when compared to random samples of NYSE/ASE securities. This suggests that samples of NASDAQ securities will exhibit far more days of zero trading volume when compared to samples of NYSE/ASE securities and that NASDAQ trading volume measures may depart more from normality than those of NYSE/ASE securities. This has important implications for parametric test statistics that are based on the assumption of normality.

Another contribution of our study is that we compare the performance of a nonparametric test statistic with the parametric test statistic used in Ajinkya and Jain (1989) and Cready and Ramanan (1991). The appealing feature of the nonparametric test statistic is that unlike the parametric test statistic, it does not require normality to achieve proper specification under the null hypothesis. Our rationale for entertaining the nonparametric test statistic in the trading volume setting stems from the results of recent return-based studies (see e.g., Corrado (1989) and Campbell and Wasley (1993)) which have found it to be more powerful in detecting abnormal security return performance when compared to the parametric test statistic used by Ajinkya and Jain (1989) and Cready and Ramanan (1991). The nonparametric test statistic's superiority over the parametric test statistic in the returns case has been documented even where departures from normality are not pronounced (see Corrado

(1989)). Thus, it's use in the trading volume setting is potentially advantageous even though Ajinkya and Jain (1989) and Cready and Ramanan (1991) find that the log-transformed trading volume measures of NYSE securities are approximately normally distributed.

Our main findings can be summarized as follows. We find the nonparametric test statistic has more power to detect abnormal trading volume than the parametric test statistic in both samples of NYSE/ASE and NASDAQ securities. This finding leads us to recommend that researchers use the nonparametric test statistic in future trading volume studies. We also document that rejection rates are greater in samples of NYSE/ASE securities compared to NASDAQ securities. Thus, abnormal trading volume will be easier to detect in samples of NYSE/ASE securities. Other findings of our study include the following. Unlike NYSE/ASE securities, for NASDAQ securities the number of shares traded does not increase monotonically as a function of firm size. Also unlike NYSE/ASE securities, the percentage of outstanding shares traded of individual NASDAQ securities continues to exhibit considerable skewness even after log-transformation. Finally, in both samples of NYSE/ASE and NASDAQ securities, the mean abnormal trading volume measures of portfolios of 20 securities or less exhibit significant departures from normality. For portfolio sizes of 50 or more securities, mean abnormal trading volume measures are approximately normally distributed.

The article is organized as follows. Section 2 describes our experimental design. Section 3 provides descriptive statistics of the daily trading volume measures of NYSE/ASE and NASDAQ securities, along with descriptive statistics of the test statistics under the null hypothesis of zero abnormal trading volume. Results of comparing the specification and power of the two test statistics are reported in section 4. Section 5 summarizes the results of sensitivity analyses, and section 6 contains a summary.

2. Experimental design

2.1. Sample

The data used in our simulations consists of random samples of 25,000 NYSE/ASE securities and 25,000 NASDAQ securities. These samples are constructed by sampling with replacement from the population of securities listed on the CRSP NYSE/ASE and NASDAQ daily files. Each time a security is selected an event date (day 0) between 1/1/84 and 12/31/91 is randomly generated. For each security we extract a time series of 250 days of trading volume and shares outstanding data. A 250-day sample period provides sufficient data for the alternative estimation periods we examine. A security with zero trading volume or missing trading volume for more than 40 days during the 250-day sample period, or with missing trading volume data on the event day, is dropped and another security is selected in its place. We use these randomly selected securities to form portfolios ranging in size from 5 to 100 securities for use in our simulation analysis.

2.2. Measures of abnormal trading

The trading volume metric underlying our simulations is the percentage of outstanding shares traded on a given day:

$$V_{it} = \frac{(n_{it} \times 100)}{S_{it}} \tag{1}$$

where n_{it} is the number of shares traded for firm i on day t, and S_{it} is the firm's outstanding shares on day t. The results in Ajinkya and Jain (1989) and Cready and Ramanan (1991) clearly document the importance of using a log-transformation of raw trading volume. Accordingly, in our simulations we use the natural log of the percentage of outstanding shares traded metric appearing in equation (1). Before transformation we add the small constant of .000255 to preclude taking the log of zero in the case of zero trading volume on a given day (see Cready and Ramanan (1991)). The log-transformed percentage of shares traded metric we use is identical to that used in Cready and Ramanan (1991) and similar to the metric Ajinkya and Jain (1989) referred to as the fraction of outstanding shares traded.

We use the same three approaches to estimate expected trading volume as Ajinkya and Jain (1989) and Cready and Ramanan (1991). They are mean-adjusted trading volume, an ordinary least squares market model in trading volume, and an estimated generalized least squares (EGLS) version of a market model in trading volume corrected for first-order autocorrelation (see Judge et al. (1985)).

Mean-adjusted abnormal trading volume is:

$$v_{it} = V_{it} - \bar{V}_i, \tag{2}$$

where

$$\bar{V}_i = \frac{1}{T} \sum_{t=f}^{t=l} V_{it}, \tag{3}$$

T is the number of days in the estimation period and $f(l)$ is the first (last) day of the estimation period. To facilitate comparison with prior studies we use 100-, 170- and 238-day estimation periods. In all three cases, one-half of the estimation period is drawn from the period prior to the event date and the other half from the period after the event date. For example, with day 0 denoting the event date, a 100-day (238-day) estimation period would use days -55 to -6 and $+6$ to $+55$ (-124 to -6 and $+6$ to $+124$). To save space, the main results, which are reported in section 4, use a 100-day estimation period. Results for the 170- and 238-day estimation periods are summarized as part of the sensitivity analyses in section 5.

Market model abnormal trading volume is:

$$v_{it} = V_{it} - (\alpha_i + \beta_i V_{mt}), \tag{4}$$

where α_i and β_i are obtained via ordinary least squares (OLS) estimation. The market volume measure for a given day t is measured as:

$$V_{mt} = \frac{1}{N} \sum_{i=1}^{N} V_{it}, \tag{5}$$

where N is the number of securities in the market index.

EGLS market model abnormal trading volume is:

$$v_{it} = V_{it} - (\alpha_i^* + \beta_i^* V_{mt}). \tag{6}$$

The parameters α_i^* and β_i^* result from a two-step estimation procedure. The first step is the usual OLS market model estimation process. The residuals that result from this estimation are used to generate autocorrelations which are then used to transform the original data to exploit the autocorrelation structure in parameter estimation and prediction. Least squares estimation on the transformed data yield the estimates α_i^* and β_i^* (for additional details see Judge, et al. (1985)).

2.3. *Inducing abnormal trading volume*

We induce abnormal trading volume using the multiplicative inducement procedure described in Cready and Ramanan (1991).[1] Under the multiplicative inducement procedure post-inducement log-transformed volume is equal to $\log((1 - p)V)$, where p denotes the percentage increase in raw volume and V is the raw volume metric prior to induced abnormal trading. The expression for post-induced volume simplifies to $\log(p) + \log(V)$, implying that induced abnormal trading volume is a constant. In our simulations we examine cases where p varies from 0.0 to 0.5.

2.4. *Test statistics*

We study the performance of two alternative test statistics. The first is the parametric test statistic analyzed by both Ajinkya and Jain (1989) and Cready and Ramanan (1991). We refer to this statistic as the portfolio test statistic. It is:

$$\frac{\bar{v}_t}{s(\bar{v}_t)}, \tag{7}$$

where $\bar{v}_t$ is the equal-weighted portfolio mean abnormal trading volume on the event date,

$$\bar{v}_t = \frac{1}{N} \sum_{i=1}^{N} v_{it},$$

$$s(\bar{v}_t) = \sqrt{\frac{1}{T} \sum_{t=f}^{t=l} (\bar{v}_t - \bar{\bar{v}})^2}. \tag{8}$$

$\bar{\bar{v}}$ is the mean of the $\bar{v}_t$ over the estimation period ($\bar{\bar{v}} = 1/T \, \Sigma_{t=f}^{t=l} \bar{v}_t$). The standard deviation in (8) is estimated using time-series data from the estimation period, which means it explicitly accounts for any cross-sectional dependence in abnormal trading volume. If the v_{it} are normal, independent, and identically distributed random variables this test statistic is distributed student t with $T - 1$ degrees of freedom, and is approximately unit normal under the null hypothesis.

The second test statistic we examine is a nonparametric rank statistic (see Corrado (1989)). The rank statistic transforms each security's time series of abnormal trading volume into their respective ranks, thus precluding test statistic misspecification due to asymmetry in the cross section of abnormal trading volume. The appeal of the rank statistic is that unlike the portfolio test statistic, it does not require normality to achieve proper specification under the null hypothesis. Recent return-based simulation studies (see e.g., Corrado (1989) and Campbell and Wasley (1993)) have documented the rank statistic to be more powerful in detecting abnormal performance when compared to the portfolio test statistic.

The nonparametric rank statistic is the ratio of the mean deviation of the securities' day 0 ranks (k_{i0}) to the estimated standard deviation of the portfolio mean abnormal rank:

$$\frac{\frac{1}{N}\sum_{i=1}^{N}(k_{i0} - E(k_i))}{s(k)}$$

$E(k_i)$ is the expected rank for security i which is equal to $[.5T_i' + .5]$ and T_i' is the number of nonmissing trading days for firm i in the estimation and event periods. The standard deviation of the portfolio mean abnormal volume rank is:

$$s(k) = \sqrt{\frac{1}{T_i'}\sum_{t=1}^{t=T_i'}\left(\frac{1}{N}\sum_{i=1}^{N}(k_{it} - E(k_i))\right)^2} \tag{10}$$

where $k_{it} = \text{rank}(v_{it}, t = f, \ldots, l)$. The rank statistic converges to unit normal as the number of securities in the portfolio increases.

2.5. *A comparison of the portfolio and rank statistics*[2]

Lehmann (1975) and Hettmansperger (1984) show that the asymptotic relative efficiency of a rank test to a parametric t-test is stated by:

$$ARE\ (R,\ T) = 12\sigma^2\left(\int_{-\infty}^{+\infty} f^2(x)\,dx\right)^2 \tag{11}$$

where $f(x)$ is the density function of the underlying data; and σ^2 is the variance. The relative efficiency in (11) is invariant across the mean and variance of the variable x. Therefore, we standardize x and set $\sigma^2 = 1$ and $E(x) = 0$. The effect of nonnormal skewness and kurtosis in the data can be examined using a Gramm-Charlier series approximation of the density function $f(x)$ (see Stuart and Ord (1987)). The approximating density function is:

$$f(x) \approx \frac{e^{-x^2/2}}{\sqrt{2\pi}} \left[+ \frac{u_3}{6}(x^3 - 3x) + \frac{u_4 - 3}{24}(x^4 - 6x^2 + 3) \right], \tag{12}$$

where u_3 = skew (x) and u_4 = kurt (x) are coefficients of skewness and kurtosis for the underlying data. Based on the approximating density function in (12), a modestly tedious derivation yields this expression for the approximating asymptotic relative efficiency in (11).

$$ARE\,(R, T) \approx \frac{3}{\pi} \left[+ \frac{5}{96}(u_3^2) + \frac{105}{96^2}(u_4 - 3)^2 + \frac{u_4 - 3}{16} \right]^2 \tag{13}$$

Values of $ARE\,(R, T)$ greater than one indicate a greater efficiency for the rank test. For normal data where $u_3 = 0$ and $u_4 = 3$ we obtain $ARE\,(R, T) \approx 0.955$. For the nonnormally distributed NYSE/ASE log-transformed trading volume as a percent of outstanding shares traded reported below in panel A of table 1 we have $u^3 = -0.185$ and $u_4 = 4.13$, from which we obtain $ARE\,(R, T) \approx 1.128$. For the NASDAQ log-transformed trading volume data reported below in panel B of table 1 we have $u_3 = -0.71$ and $u_4 = 4.63$, from which we obtain $ARE\,(R, T) \approx 1.281$. Thus, we expect the rank test to be superior to the parametric t-test in the trading volume setting because of the nonnormal characteristics of the underlying data.

3. Preliminary results

3.1. Properties of daily trading volume for individual securities

Panels A and B of table 1 present summary statistics based on the 25,000 security NYSE/ASE and NASDAQ samples, respectively. Summary statistics are reported for the number of shares traded and percentage of outstanding shares traded, both before and after taking a natural log-transformation. Means and standard deviations are presented for deciles formed on the basis of firm size measured as the market value of equity. The bottom of each panel reports descriptive statistics for each sample as a whole. The values reported for mean, standard deviation, skewness, and kurtosis are averages of the underlying 25,000 individual security means, standard deviations, skewness, and kurtosis coefficients estimated using data from the 100-day estimation period. Kurtosis coefficients reflect the subtraction of 3.0 which is the expected value under normality.

The results in panel A for NYSE/ASE securities reveal that the mean number of shares traded increases monotonically with firm size. This is not so for the percentage of outstanding shares traded. These findings are similar to what Cready and Ramanan (1991) report. The full sample summary statistics at the bottom of panel A indicate that the untransformed trading volume measures are considerably nonnormal; skewness and kurtosis coefficients are 3.3 and 17.0, respectively, for both the number of shares traded and the percent of outstanding shares traded. After a natural log-transformation average skewness declines to −0.51 and −0.185, and average kurtosis to 3.1 and 1.13, for the number of shares traded and the percent of outstanding shares traded, respectively. Thus, consistent with

Table 1. Panel A. Descriptive statistics for daily trading volume for firm size deciles[a] and for the full sample[b]; 25,000 randomly selected event dates between 1/1/84 and 12/31/91; NYSE/ASE securities.

Deciles Based on Market Value of Outstanding Common Shares	Firm Size (Market Value of Common Shares Outstanding in $ Millions)	Untransformed Volume Measures[a]		Log-Transformed Volume Measures[a]	
		Number of Shares Traded (1,000s)	Percent of Outstanding Shares Traded	Number of Shares Traded (1,000s)	Percent of Outstanding Shares Traded
	Mean	Mean (Standard Deviation)	Mean (Standard Deviation)	Mean (Standard Deviation)	Mean (Standard Deviation)
Smallest	17.1	9.4 (13.1)	0.216 (0.302)	0.967 (1.79)	-2.53 (1.42)
	44.4	14.6 (19.2)	0.197 (0.264)	1.51 (1.42)	-2.45 (1.18)
	76.6	19.6 (24.2)	0.205 (0.260)	1.87 (1.25)	-2.38 (1.08)
	120.2	28.7 (34.9)	0.235 (0.294)	2.32 (1.12)	-2.23 (1.01)
	192.7	41.2 (47.9)	0.246 (0.298)	2.67 (1.06)	-2.19 (0.978)
	321.3	58.8 (65.6)	0.246 (0.284)	3.07 (1.10)	-2.18 (0.939)
	548.8	85.2 (89.2)	0.257 (0.276)	3.61 (0.892)	-2.04 (0.859)
	978.8	148.1 (158.2)	0.290 (0.314)	4.30 (0.800)	-1.84 (0.786)
		247.9 (233.1)	0.290 (0.271)	4.90 (0.710)	-1.73 (0.698)
Largest	11,541.0	572.0 (391.8)	0.260 (0.190)	5.68 (0.62)	-1.94 (0.58)
All Firms[b]					
Average mean		122.6	0.244	3.09	-2.15
Average standard deviation		107.7	0.275	1.07	0.95
Average skewness		3.3	3.3	-0.51	-0.185
Average kurtosis		17.0	17.0	3.1	1.13

[a] Firm size decile means are averages of individual security means calculated over the 100-day period centered on the event date (day 0). Similarly, firm size decile standard deviations are averages of individual security standard deviations calculated over the 100-day period centered on the event date (day 0).
[b] All firm statistics are averages of the means, standard deviations, skewness, and kurtosis coefficients of individual securities calculated over the 100-day period centered on the event date (day 0). Kurtosis coefficients reflect the subtraction of 3.0 which is the expected value under normality.

prior studies, a natural log-transformation almost eliminates the departure from normality of raw trading volume measures. On balance, our results for NYSE/ASE securities are similar to those Ajinkya and Jain (1989) and Cready and Ramanan (1991) report for NYSE securities, except that we observe slightly more skewness in log-transformed trading volume.

Results in panel B for NASDAQ securities indicate that the number of shares traded does not increase monotonically as a function of firm size. This is unlike the behavior of NYSE/ASE trading volume. The full-sample summary statistics at the bottom of panel B reveal that the untransformed trading volume measures of NASDAQ securities are considerably nonnormal. The average skewness and kurtosis coefficients are 3.3 and 16.5,

Table 1. Panel B. Descriptive statistics for daily trading volume for firm size deciles[a] and for the full sample[b]; 25,000 randomly selected event dates between 1/1/84 and 12/31/91; NASDAQ securities.

Deciles Based on Market Value of Outstanding Common Shares	Firm Size (Market Value of Common Shares Outstanding in $ Millions)	Untransformed Volume Measures[a]		Log-Transformed Volume Measures[a]	
		Number of Shares Traded (1,000s)	Percent of Outstanding Shares Traded	Number of Shares Traded (1,000s)	Percent of Outstanding Shares Traded
	Mean	Mean (Standard Deviation)	Mean (Standard Deviation)	Mean (Standard Deviation)	Mean (Standard Deviation)
Smallest	6.6	22.6	0.362	1.36	-2.30
		(28.3)	(0.521)	(2.15)	(1.65)
	13.5	19.7	0.336	1.47	-2.18
		(24.5)	(0.441)	(1.91)	(1.52)
	20.9	20.0	0.348	1.62	-2.11
		(25.1)	(0.476)	(1.76)	(1.44)
	30.0	21.1	0.367	1.79	-2.04
		(27.7)	(0.503)	(1.70)	(1.41)
	42.0	25.9	0.394	1.99	-1.97
		(33.6)	(0.537)	(1.61)	(1.36)
	59.5	36.2	0.422	2.26	-1.90
		(44.5)	(0.555)	(1.52)	(1.30)
	89.8	43.2	0.434	2.49	-1.86
		(53.1)	(0.556)	(1.46)	(1.26)
8	147.2	57.6	0.435	2.71	-1.90
		(67.5)	(0.530)	(1.45)	(1.24)
	253.2	83.6	0.420	3.17	-1.86
		(88.8)	(0.466)	(1.27)	(1.12)
Largest	941.0	264.6	0.485	4.27	-1.57
		(216.9)	(0.440)	(0.942)	(0.900)
All Firms[b]					
Average mean		59.5	0.400	2.31	-1.97
Average standard deviation		61.0	0.503	1.58	1.32
Average skewness		3.3	3.3	-1.33	-0.71
Average kurtosis		16.5	16.5	5.2	1.63

[a] Firm size decile means are averages of individual security means calculated over the 100-day period centered on the event date (day 0). Similarly, firm size decile standard deviations are averages of individual security standard deviations calculated over the 100-day period centered on the event date (day 0).

[b] All firm statistics are averages of the means, standard deviations, skewness, and kurtosis coefficients of individual securities calculated over the 100-day period centered on the event date (day 0). Kurtosis coefficients reflect the subtraction of 3.0 which is the expected value under normality.

respectively, for both the number of shares traded and the percent of outstanding shares traded. These values are similar to those reported for NYSE/ASE securities. While a natural log-transformation eliminated much of the nonnormality in the NYSE/ASE data, considerable evidence of nonnormality remains in NASDAQ trading volume even after a natural log-transformation. The average skewness coefficient is -1.33 and -0.71 for the number of shares traded and the percent of outstanding shares traded, respectively. Corresponding average kurtosis coefficients are 5.2 and 1.63, respectively. Thus, even after a log-transformation, the daily trading volume of NASDAQ securities still exhibits considerable skewness and kurtosis.

Other interesting differences between NYSE/ASE and NASDAQ daily trading volume include the following. The mean number of shares traded for the NASDAQ sample of 59,500 is less than half the mean of 122,600 for the NYSE/ASE sample. However, the average percent of outstanding shares traded for the NASDAQ sample is .40% compared to .24% for the NYSE/ASE sample. Also worth noting is that the log-transformed trading volume measures of NASDAQ securities exhibit greater variability compared to NYSE/ASE securities. The average standard deviation of the log-transformed number of shares traded in the NASDAQ sample is 1.58 compared to 1.07 for the NYSE/ASE sample. Corresponding average standard deviations for log-transformed percentage of outstanding shares traded are 1.32 and .95, respectively.

3.2. *Properties of portfolio abnormal trading volume on the event date (day 0)*

The descriptive statistics reported in table 1 reveal a tendency for skewness in the actual (log-transformed) trading volume of individual NYSE/ASE and NASDAQ securities. Since hypothesis tests typically focus on mean abnormal trading volume rather than actual raw trading volume, a more important concern is the extent to which portfolio mean abnormal trading volume measures exhibit significant departures from normality. In this section we provide evidence on how rapidly portfolio mean abnormal trading volume measures converge to normality as the number of securities in the portfolio increases. Panels A (NYSE/ASE) and B (NASDAQ) of table 2 provide univariate statistics of the mean abnormal trading volume on day 0 (i.e., the event date) for portfolios ranging in size from 5 to 100 securities when no abnormal trading has been induced. Abnormal trading is measured using the mean-adjusted, OLS, and EGLS models of expected trading volume.

The results for NYSE/ASE securities indicate significant skewness in portfolios of 20 securities or less. In all cases the skewness coefficients are significantly different than that expected under normality (i.e., 0) at the 1% level.[3] Additional evidence of departures from normality in portfolios of 10 securities or less is that kurtosis coefficients are all significantly greater than their expected value (i.e., 3) at the 1% level. For portfolio sizes of 50 securities (or more) mean abnormal trading volume seems close to normal. Turning to panel B and the results for NASDAQ securities reveals the results are very similar to those for NYSE/ASE securities. Portfolios of size 20 or less exhibit significant skewness; kurtosis coefficients for portfolios of 10 securities or less are significantly greater than expected under normality; and portfolio sizes of 50 (or more) appear to be normally distributed. Other features of the results in table 2 that are worth noting include the following. As expected, the standard deviations of portfolio mean abnormal trading volume measures decrease as portfolio size increases. This means the power of the test to detect abnormal trading volume will be greater the larger the portfolio size. Also, for any given portfolio size, the standard deviations of portfolio mean abnormal trading volume measures are smaller for NYSE/ASE securities when compared to NASDAQ securities. This means that for a given portfolio size, abnormal trading volume will be easier to detect in samples of NYSE/ASE securities when compared to samples of NASDAQ securities.

Table 2. Cross-sectional properties of daily abnormal trading volume measures for NYSE/ASE securities (panel A) and NASDAQ securities (panel B) on the event date (day 0). No abnormal trading has been induced. The trading volume measure is the natural log of the percentage of outstanding shares traded. The numbers reported in the table for mean abnormal trading, standard deviation, skewness, kurtosis, and studentized range are averages from the number of portfolios indicated.

Panel A: NYSE/ASE Securities

Number of Securities in Portfolio	Number of Portfolios	Model[a]	Mean Abnormal Trading	Standard Deviation	Skewness[b]	Kurtosis[b]	Studentized Range
			.0000				
			.0000				
			.0000				
10	2.500		.0000				
			.0000				
			.0000				
20	1,250		.0000				
			.0000				
			.0000				
50	500		.0000				
			.0000				
			.0000				
100	250		.0000				
			.0000				
			.0000				

Panel B: NASDAQ Securities

Number of Securities in Portfolio	Number of Portfolios	Model[a]	Mean Abnormal Trading	Standard Deviation	Skewness[b]	Kurtosis[b]	Studentized Range
5	5,000	Mean-Adjusted	.0000				
		OLS	.0000				
		EGLS	.0000				
10	2.500	Mean-Adjusted	.0000				
		OLS	.0000				
		EGLS	.0000				
20	1,250	Mean-Adjusted	.0000				
		OLS	.0000				
		EGLS	.0000				
50	500	Mean-Adjusted	.0000				
		OLS	.0000				
		EGLS	.0000				
100	250	Mean-Adjusted	.0000				
			.0000				
			.0000				

[a]Expected trading volume models are based on a 100-day estimation period. Under the mean-adjusted method, expected volume equals mean volume estimated over days −55 to −6 and +6 to +55 relative to the event date (day 0). Under the OLS market model, expected volume is estimated from a time-series regression (same estimation period as the mean-adjusted method) where the dependent variable is the natural log of the firm's percentage of outstanding shares traded and the independent variable is the natural log of the percentage of outstanding shares traded for an equal-weighted index comprised of NYSE/ASE securities (panel A) or NASDAQ securities (panel B). The EGLS method is similar to the OLS market model except that the estimation is subject to correction for first-order serial correlation (see Judge et al. (1985)).

[b]To test for significant departures from normality we construct a Z-test for each skewness and kurtosis coefficient. The expected skewness and kurtosis of a normal distribution are 0 and 3.0, respectively. The Z-statistic is defined as the skewness (or kurtosis) coefficient reported in the table minus its expected value (0 or 3.0, respectively), divided by its standard deviation. The standard deviation of the sample coefficients of skewness and kurtosis are $\sqrt{6/n}$ and $\sqrt{24/n}$, respectively, where n is the number of portfolios (see Stuart and Ord (1987)).

*Significantly different from the expected value at the 1% level.

**Significantly different from the expected value at the 5% level.

3.3. Properties of the test statistics in the absence of induced trading volume

In this section we provide evidence of how closely the empirical distribution of each test statistic corresponds to its theoretical unit normal distribution under the null hypothesis. This allows us to gauge the impact on proper test statistic specification of the excessive skewness and kurtosis in portfolio mean abnormal trading volume documented in table 2. Table 3 reports univariate statistics of the cross-sectional distribution of each test statistic on day 0 when no abnormal trading has been induced. Results are separately reported for portfolios of size 10, 50, and 100 NYSE/ASE and NASDAQ securities for three models of expected trading volume.

Focusing first on the behavior of the portfolio test statistic, significant departures from the theoretical unit normal distribution are evident. Skewness and kurtosis coefficients for portfolios of 10 NYSE/ASE securities are significantly different from their expected values under normality (0 and 3, respectively) at the 1% level. Similar results are observed in samples of 10 NASDAQ securities except that under the EGLS model of expected volume the kurtosis coefficient is no longer significant. Further evidence of significant skewness in the portfolio test statistic occurs in samples of 50 NASDAQ securities. The only other evidence of misspecification is in samples of 100 NASDAQ securities (OLS market model) where the kurtosis coefficient is significantly greater than its expected value at the 5% level. Contrary to the results for the portfolio test statistic, the results for the rank statistic reveal no evidence of nonnormality. In no case is a skewness or kurtosis coefficient significantly different from its expected value under normality. A final feature of the results worth noting is that the means of the test statistics are always positive for portfolios of NYSE/ASE securities, but generally negative for portfolios of NASDAQ securities. This difference would appear to reflect a greater frequency of days with little or no trading volume for NASDAQ securities vis-a-vis NYSE/ASE securities. In summary, the results indicate that the rank statistic conforms quite well to its theoretical unit normal distribution under the null hypothesis, while the portfolio test statistic is subject to some misspecification. The simulation results reported in the next section will gauge whether the observed departures from normality lead to excessive type I error rates for the portfolio test statistic.

4. Results of simulation analysis

The results reported in this section are for portfolio sizes of 10, 50, and 100 securities using a one-day event period. The null hypothesis is that the event day's mean abnormal trading volume is zero. Abnormal volume is induced as a fraction of each security's event date (pre-log-transformed) trading volume. The level of induced trading ranges from 0% to 50% of pre-log-transformed trading volume. Rejection rates are based on a 5% one-tailed test and expected volume is estimated using a 100-day estimation period. Results for longer estimation periods and for a 1% one-tailed test are summarized in section 5.

4.1. NYSE/ASE securities

Rejection rates for the portfolio and rank statistics for portfolios of NYSE/ASE securities are reported in table 4. In the absence of induced trading volume, the rejection rates for

Table 3. Univariate statistics of the cross-sectional distribution of the portfolio and rank statistics for portfolios of NYSE/ASE and NASDAQ securities. No abnormal trading has been induced. The trading volume measure is the natural log of the percentage of outstanding shares traded. The numbers reported in the table for mean, standard deviation, skewness, kurtosis, and studentized range are for the cross-sectional distribution of the test statistic on the event date (day 0).

				NYSE/ASE Securities					NASDAQ Securities				
Test Statistic	Number of Securities	Number of Portfolios	Model[a]	Mean	Standard Deviation	Skewness[b]	Kurtosis[b]	Studentized Range	Mean	Standard Deviation	Skewness[b]	Kurtosis[b]	Studentized Range
Portfolio[c]	10	2,500	Mean-Adjusted	0.017	1.01	−0.248*	3.46*	8.21	−0.025	1.00	−0.337*	3.23**	6.89
			OLS	0.021	1.02	−0.231*	3.52*	8.35	−0.015	1.02	−0.347*	3.24**	7.13
			EGLS	0.023	1.00	−0.224*	3.48*	8.08	−0.001	0.98	−0.374*	3.18	6.74
	50	500	Mean-Adjusted	0.034	1.01	−0.173	2.91	6.36	−0.060	0.99	−0.299*	3.18	6.32
			OLS	0.042	1.04	−0.104	2.91	6.23	−0.038	1.02	−0.302*	3.17	6.17
			EGLS	0.047	1.01	−0.033	3.07	6.65	−0.009	0.98	−0.304*	3.10	5.88
	100	250	Mean-Adjusted	0.056	1.02	−0.112	2.85	5.71	−0.084	1.03	−0.223	3.50	6.48
			OLS	0.064	1.02	−0.064	2.80	5.70	−0.054	1.06	−0.282	3.75**	6.87
			EGLS	0.075	1.00	−0.089	3.16	6.13	−0.011	1.01	−0.183	3.43	6.47
Rank[d]	10	2,500	Mean-Adjusted	0.020	0.98	−0.002	2.85	6.42	−0.022	0.98	−0.019	2.88	6.82
			OLS	0.020	0.98	−0.012	2.88	6.14	−0.004	0.99	−0.036	2.88	6.52
			EGLS	0.037	0.98	−0.018	2.91	6.55	0.003	0.97	−0.078	2.84	6.85
	50	500	Mean-Adjusted	0.048	0.99	−0.178	2.67	5.70	−0.051	0.94	0.038	2.77	5.32
			OLS	0.048	1.02	−0.151	2.90	6.15	−0.010	0.95	−0.011	2.85	5.46
			EGLS	0.083	1.02	−0.073	2.96	6.30	0.003	0.93	−0.042	2.74	5.67
	100	250	Mean-Adjusted	0.074	1.03	−0.170	2.52	5.00	−0.068	0.98	0.064	3.33	6.15
			OLS	0.070	1.02	−0.070	2.75	5.78	−0.013	0.98	−0.016	3.42	6.42
			EGLS	0.124	1.02	−0.049	2.98	5.88	0.005	0.97	0.036	3.36	6.39

[a]Expected trading volume models are based on a 100-day estimation period. Under the mean-adjusted method, expected volume equals mean volume estimated over days −55 to −6 and +6 to +55 relative to the event date (day 0). Under the OLS market model, expected volume is estimated from a time-series regression (same estimation period as the mean-adjusted method) where the dependent variable is the natural log of the firm's percentage of outstanding shares traded and the independent variable is the natural log of the percentage of outstanding shares traded for an equal-weighted index comprised of NYSE/ASE securities (panel A) or NASDAQ securities (panel B). The EGLS method is similar to the OLS market model except that the estimation is subject to correction for first-order serial correlation (see Judge et al. (1985)).

[b]To test for significant departures from normality we construct a Z-test for each skewness and kurtosis coefficient. The expected skewness and kurtosis of a normal distribution are 0 and 3.0, respectively. The Z-statistic is defined as the skewness (or kurtosis) coefficient reported in the table minus its expected value (0 or 3.0, respectively), divided by its standard deviation. The standard deviation of the sample coefficients of skewness and kurtosis are $\sqrt{6/n}$ and $\sqrt{24/n}$, respectively, where n is the number of portfolios (see Stuart and Ord (1987)).

[c]The portfolio test statistic is the portfolio's mean daily abnormal trading volume, divided by its estimated standard deviation. See section 2.4 for details.

[d]The rank statistic is the portfolio's mean daily abnormal rank, divided by its estimated standard deviation. See section 2.4 for details.

*Significantly different from the expected value at the 1% level.

**Significantly different from the expected value at the 5% level.

Table 4. A comparison of alternative test statistics for detecting abnormal trading volume in samples of NYSE/ASE securities. The null hypothesis is that mean abnormal trading volume on the event date (day 0) is zero. The trading volume measure is the natural log of the percentage of outstanding shares traded. Induced volume is the indicated percent of pre-log-transformed trading volume. The rejection rule is a 5% one-tailed test. Results are for randomly selected event dates from 1/1/84 through 12/31/91.

			Portfolio Test Statistic[a]						Rank Test Statistic[b]					
			Level of Induced Trading (%)						Level of Induced Trading (%)					
Securities	Portfolios	Model[c]	0	10	20	30	40	50	0	10	20	30	40	50
10	2,500	Mean-Adjusted	4.3	8.7	13.4	21.0	28.4	37.2	4.6	9.1	17.1	26.4	36.6	46.8
		OLS	5.0	9.4	14.8	21.7	30.4	38.8	4.9	9.8	17.6	27.8	38.8	49.4
		EGLS	4.4	8.6	14.3	21.6	30.0	39.6	4.8	10.5	18.4	29.2	40.0	50.8
50	500	Mean-Adjusted	3.8	18.0	38.6	58.8	74.6	87.2	4.0	23.6	50.4	75.6	88.8	94.6
		OLS	5.4	21.0	41.6	60.8	77.0	89.4	5.0	23.8	52.8	77.4	90.4	97.2
		EGLS	5.4	19.0	38.4	59.2	78.2	89.0	5.6	25.0	55.0	79.8	91.6	97.2
100	250	Mean-Adjusted	4.4	28.0	58.8	80.8	96.8	98.8	5.6	40.0	72.4	92.0	98.0	100
		OLS	5.2	31.2	59.2	84.0	96.4	99.2	5.6	38.4	78.0	94.0	99.6	100
		EGLS	5.6	24.8	56.8	87.6	96.4	99.2	7.6	38.8	79.2	95.2	99.6	100

[a] The portfolio test statistic is the portfolio's mean daily abnormal trading volume, divided by its estimated standard deviation. See section 2.4 for details.

[b] The rank statistic is the portfolio's mean daily abnormal rank, divided by its estimated standard deviation. See section 2.4 for details.

[c] Expected trading volume models are based on a 100-day estimation period. Under the mean-adjusted method, expected volume equals mean volume over days −55 to −6 and +6 to +55 relative to the event date (day 0). Under the OLS market model, expected volume is estimated from a time-series regression (same estimation period as the mean-adjusted method) where the dependent variable is the natural log of the firm's percentage of outstanding shares traded and the independent variable is the natural log of the percentage of outstanding shares traded for an equal-weighted index comprised of NYSE/ASE firms. The EGLS method is similar to the OLS market model except that the estimation is subject to correction for first-order serial correlation (see Judge et al. 1985)).

both test statistics are close to the 5% significance level of the test. All rejection rates fall within the 95% confidence interval for the expected 5% rate, leading us to conclude that both test statistics are well-specified in NYSE/ASE samples.

The rejection rates when abnormal trading has been induced reveal a very compelling feature. In samples of NYSE/ASE securities, regardless of portfolio size, the level of induced trading volume, or the model of expected volume; the rejection rate reported for the rank statistic always exceeds the corresponding rate reported for the portfolio test statistic. Stated differently, the rank statistic is always more powerful than the portfolio test statistic. For example, in portfolios of 50 securities with induced trading of 30%, the rejection rates for the rank statistic are 75.6%, 77.4%, and 79.8%, respectively, for the mean-adjusted, OLS market model, and EGLS model of expected trading volume. Corresponding rejection rates for the portfolio test statistic are 58.8%, 60.8% and 59.2%. The results in table 4 also indicate that the EGLS model is the preferred method to estimate expected trading volume when the rank statistic is used. In only one case (portfolios of 100 securities with 10% induced trading) is the rejection rate based on the EGLS model exceeded by one of the other models of expected volume. Under the portfolio test statistic, the OLS market model generally performs the best. However, since the portfolio test statistic is always inferior to the rank statistic, we do not pursue this issue any further. In summary, the results in table 4 clearly document the superiority of the rank statistic over the portfolio statistic in samples of NYSE/ASE securities.

4.2. NASDAQ securities

Rejection rates for the portfolio and rank statistics for portfolios of NASDAQ securities are reported in table 5. In the absence of induced trading volume, the results are similar to those found for NYSE/ASE securities. Rejection rates for both test statistics are close to the 5% significance level of the test, and all fall within the 95% confidence interval for the expected 5% rates. This leads us to conclude that both test statistics are well-specified in NASDAQ samples as well as NYSE/ASE samples.

Also similar to results for NYSE/ASE securities is that when abnormal trading volume is induced in NASDAQ securities, the rank statistic is always more powerful in detecting it compared to the portfolio test statistic. For example, in portfolios of 100 securities with induced trading of 40%, the rejection rates for the rank statistic are 88.4%, 90.0%, and 92.4%, respectively, for the mean-adjusted, OLS market model, and EGLS model of expected trading. Corresponding rejection rates for the portfolio test statistic are 74.0%, 73.2%, and 76.0%. Also evident from table 5 is that, except for a couple of cases, the EGLS model of expected trading volume continues to be preferred when the rank statistic is used. The exceptions are modest and occur in portfolios of 10 securities with 10% and 20% induced trading. In summary, the results in table 5 clearly document the superiority of the rank statistic over the portfolio statistic in samples of NASDAQ securities.

Table 5. A comparison of alternative test statistics for detecting abnormal trading volume in samples of NASDAQ securities. The null hypothesis is that mean abnormal trading volume on the event date (day 0) is zero. The trading volume measure is the natural log of the percentage of outstanding shares traded. Induced volume is the indicated percent of pre-log-transformed trading volume. The rejection rule is a 5% one-tailed test. Results are for randomly selected event dates from 1/1/84 through 12/31/91.

			Portfolio Test Statistic[a]						Rank Test Statistic[b]					
			Level of Induced Trading (%)						Level of Induced Trading (%)					
Securities	Portfolios	Model[c]	0	10	20	30	40	50	0	10	20	30	40	50
10	2,500	Mean-Adjusted	3.7	6.0	9.4	13.4	18.4	23.2	4.4	8.3	12.2	17.2	23.6	30.0
		OLS	3.9	6.6	10.2	14.8	19.8	24.8	4.6	8.3	13.0	18.6	25.0	31.6
		EGLS	3.3	6.0	9.3	13.7	19.3	25.1	4.4	8.2	12.2	18.6	25.4	33.3
50	500	Mean-Adjusted	3.4	10.6	22.2	36.0	50.8	63.0	3.6	12.0	29.4	48.0	65.4	80.2
		OLS	4.4	11.8	23.2	39.4	53.4	65.0	4.4	13.0	29.6	52.2	68.0	82.2
		EGLS	3.6	9.8	23.2	40.0	55.0	65.6	3.6	13.8	31.2	54.0	69.6	83.4
100	250	Mean-Adjusted	4.0	14.8	32.4	52.8	74.0	84.8	4.0	18.8	44.8	73.6	88.4	97.2
		OLS	5.2	16.4	36.4	54.8	73.2	86.4	5.2	20.4	46.4	77.2	90.0	98.0
		EGLS	4.8	16.8	36.4	57.6	76.0	86.4	6.0	21.2	47.6	78.8	92.4	98.8

[a] The portfolio test statistic is the portfolio's mean daily abnormal trading volume, divided by its estimated standard deviation. See section 2.4 for details.

[b] The rank statistic is the portfolio's mean daily abnormal rank, divided by its estimated standard deviation. See section 2.4 for details.

[c] Expected trading volume models are based on a 100-day estimation period. Under the mean-adjusted method, expected volume equals mean volume over days −55 to −6 and +6 to +55 relative to the event date (day 0). Under the OLS market model, expected volume is estimated from a time-series regression (same estimation period as the mean-adjusted method) where the dependent variable is the natural log of the firm's percentage of outstanding shares traded and the independent variable is the natural log of the percentage of outstanding shares traded for an equal-weighted index comprised of NYSE/ASE firms. The EGLS method is similar to the OLS market model except that the estimation is subject to correction for first-order serial correlation (see Judge et al. 1985)).

Comparing the results in table 4 (NYSE/ASE) with those in table 5 (NASDAQ) reveals the power of the test to detect abnormal trading volume is greater in samples of NYSE/ASE securities compared to samples of NASDAQ securities. For example, using the rank statistic in a sample of 100 securities with induced trading of 20%, rejection rates for NYSE/ASE securities are 72.4%, 78.0%, and 79.2%, respectively, for the mean-adjusted, OLS market model, and EGLS model of expected trading volume. Corresponding rejection rates for NASDAQ securities are 44.8%, 46.4%, and 47.6%, respectively. The results clearly indicate that abnormal trading volume will be detected more often in samples of NYSE/ASE securities.

5. Sensitivity analyses

To assess the sensitivity of the results reported above to variations in our basic experimental design we repeated our analysis using a 1% one-tailed significance test and using estimation periods of 170 and 238 days for expected trading volume. In this section we briefly summarize the results of these additional tests.

Our baseline results for a 100-day estimation period are robust under a 1% significance test. In the absence of induced trading, both the portfolio and rank statistics reject the null hypothesis at approximately the 1% significance level of the test. However, when abnormal trading volume is induced, the rank statistic is always more powerful in detecting it. As before, the rank statistic used in conjunction with the EGLS model of expected volume generally provides the most powerful test. These results hold for both samples of NYSE/ASE and NASDAQ securities.

With estimation periods of 170 and 238 days both test statistics remain well-specified in the absence of induced trading. This result holds for both samples of NYSE/ASE and NASDAQ securities regardless of portfolio size, method to estimate expected trading volume, or whether a 5% or 1% significance level is used. In terms of power, increasing the length of the estimation period has virtually no impact on the power of the test in samples of NYSE/ASE securities. In contrast, in samples of NASDAQ securities modest power increases in both test statistics emerge as the estimation period is increased to 238 days. However, the rank statistic continues to be more powerful than the portfolio test statistic. In summary, the results of our sensitivity tests provide additional evidence in favor of using the rank statistic in conjunction with the EGLS model of expected trading volume. These results also indicate that in samples of NASDAQ securities the power of the rank statistic can be enhanced by lengthening the estimation period to 238 days.

6. Summary and conclusions

This study extended prior research on the properties of daily trading volume in two ways. We studied the empirical properties of the daily trading volume of NASDAQ securities as well as NYSE/ASE securities. Prior studies by Ajinkya and Jain (1989) and Cready and Ramanan (1991) studied only NYSE securities. We also compared a nonparametric test statistic's power to detect abnormal trading volume with that of the parametric test statistic used in Ajinkya and Jain (1989) and Cready and Ramanan (1991). The motivation to consider the nonparametric test statistic is that unlike the parametric test statistic, it does not require normality to achieve proper specification under the null hypothesis.

We find that the nonparametric test statistic is always more powerful in detecting abnormal trading volume when compared to the parametric test statistic. This result holds in both samples of NYSE/ASE and NASDAQ securities and leads us to recommend the use of the nonparametric test statistic in future trading volume studies. Our results also show that abnormal trading volume will be easier to detect in samples of NYSE/ASE securities compared to samples of NASDAQ securities.

Other aspects of our findings that are worth noting include the following. Unlike NYSE/ASE securities, for NASDAQ securities the number of shares traded does not increase monotonically as a function of firm size. Also, even after a log-transformation, the percentage of outstanding shares traded of individual NASDAQ securities exhibits considerable skewness. Finally, in both samples of NYSE/ASE and NASDAQ securities, the mean abnormal trading volume measures of portfolios of 20 securities or less exhibit significant departures from normality. For portfolio sizes of 50 or more securities, mean abnormal trading volume measures are approximately normally distributed for both samples of NYSE/ASE and NASDAQ securities.

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Notes

1. See Cready and Ramanan (1991) for a discussion of the superiority of the multiplicative inducement procedure over the additive inducement procedure used by Ajinkya and Jain (1989).
2. We thank the referee for suggesting the analysis in this section.
3. See footnote b to table 2 for our approach to testing the significance of the skewness and kurtosis coefficients reported in tables 2 and 3.

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