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Abstract

In this paper, we re-examine the evidence of long memory in the Australian stock market. Using the rescaled range analysis, we find evidence of long memory and non-periodic cycles in the All Ordinaries Index. The result suggests that long memory is present in the Australian stock market. Furthermore, we add to the literature by investigating the presence of long memory in the daily ASX 50 index and its 50 constituent stocks using a GPH test proposed by Geweke and Porter-Hudak (1983). The results of individual stocks differ from those of the ASX 50 index and suggest that a common stock index is not representative of all market features.

Key words: long memory, persistence, rescaled range analysis, GPH test

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I. Introduction

Many studies have investigated the presence or otherwise of long memory in stock returns to question the validity of the efficient market hypothesis (EMH). Long memory series can be defined as having autocorrelations that slowly decline. This implies that shocks to returns in long memory series tend to decay much more slowly than in a short memory series where shocks to returns tend to dissipates rapidly. The presence of long memory in stock returns raises important questions for modern financial economics. Lo (1991) pointed out several important implications on the presence of long memory in asset returns. (1) Optimal consumption/savings and portfolio decisions may become extremely sensitive to the investment horizon; (2) Derivatives pricing models based on martingale methods, such as the Black-Scholes model, are no longer reliable, since the class of continuous time stochastic processes most commonly employed is inconsistent with long memory; (3) Traditional tests of the capital asset pricing model and arbitrage pricing theory are not valid since they do not take into account time series exhibiting such persistent statistical dependence. Thus, the presence or absence of long memory in stock returns would question the validity of the EMH.

Much literature has examined the evidence of long memory in stock markets worldwide. From an empirical perspective, the presence of long memory in stock markets has been inconclusive. On the one hand, some studies are supportive of the EMH. Lo (1991) suggested no evidence of the presence of long memory in the US stock market once short-term dependence is accounted for. Mills (1993) investigated monthly UK stock returns in terms of both Lo's modified R/S analysis and the GPH test. The estimates of modified R/S analysis indicated significant evidence of long memory, whereas the results of the GPH test exhibit little evidence of long memory. However, 'although there was some evidence of long memory in UK stock returns, it was not convincing due to the lack of dependence on other macroeconomic series' (Mills 1993 p. 303). Cheng and Lai (1995) examined long memory in international stock markets including the Australian stock market, using modified R/S analysis and fractional differencing test. Interestingly, it was found that the null hypothesis that Australian stock returns follow a short memory process can not be rejected so the Australian stock returns appear to follow a random walk. Howe et al. (1999), Henry (2002) and Tolvi (2003) also found little evidence of long memory in the Australian stock market. These studies are sensitive to the weak form of market efficiency and short memory in the Australian stock market.

On the other hand, critics of EMH have argued that evidence of long memory results in market inefficiency. Barkoulas et al. (2000) found significant evidence of long memory in Greek stock market, using the semi-parametric test. Cajueiro and Tabak (2004) tested the market efficiency for China, Hong Kong and Singapore in terms of rescaled range analysis. The authors found significant evidence of long memory in Chinese stock market, indicating that liquidity and capital restrictions may violate the validity of EMH. McKenzie (2001) identified evidence of long memory and non-periodic cycles in the Australian stock market in terms of classical adjusted R/S analysis. Non-periodic cycles of approximately three, six and twelve years were found in the Australian stock market. The author suggested the identification of a six-year cycle is broadly consistent with the business cycle.

The primary aim of this paper is to re-examine the evidence of long memory and some types of non-periodic cycles in the Australian stock market. In this respect, this study provides two important contributions. First, this study will examine the presence of long memory and find possible market cycles, using R/S analysis. The results of long memory can provide a broader understanding of the stock price dynamics which are characterised by non-linear behaviours. The test for long memory provides an important guideline of market efficiency since the efficient market hypothesis depends on the presence/absence of long memory in the stock returns. Additionally, the identification of market cycles gives a potential opportunity to earn abnormal returns in the stock markets. The identification of market cycles may give rise to an opportunity to gain abnormal returns for technical analysts.

Second, we examine long memory at the individual stock level. The existing work on long memory has focused on composite stock index returns or common stock index returns, such as the Dow-Jones or the S&P 500 index. However, composite stock index returns do not necessarily represent all stock market characteristics. In necessity, individual stocks need to be examined because the results relating to individual stocks might differ from that of a common stock index. Studies that compare results of long memory between composite stock index returns and individual stocks have been relatively overlooked. The analysis of long memory at the individual company level would shed light on the characteristics of individual stock returns within a single market because it is likely that the characteristics of long memory affect individual stocks in much the same manner as they do the market index. In this paper, we will compare the existence or otherwise of long memory between the daily S&P/ASX 50 index and its 50 constituent stocks in the Australian stock market using the fractional differencing test.

The paper is structured as follows. Section II discusses data and descriptive statistics. Section III presents the empirical results and Section IV offers some conclusions.

II. Data and Descriptive statistics

The two data sets used in this research consist of closing daily prices in the Australian Stock Exchange (ASX). The first data set is the All Ordinaries (All Ords) index which is a weighted average of the stock prices for 500 companies listed on ASX. The entire sample data are shown in Figure 1, which reflects the 1987 market collapse, the buoyant period of the equity market from the late 1980s to early 2000s and later on the end of the IT dot com bubble. The second data set consists of daily ASX 50 and its constituent stocks from January 1981 to

March 2005. The ASX 50 index consists of 50 high liquid stocks with significant market capitalisation. All sample prices are transformed into continuously compounded return series.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where R_t is the logarithmic return at time t, P_t is the price at time t. Descriptive statistics for our sample returns are further presented in Table 1. The most interesting finding is the fact that the all sample returns appear extremely non-normal. Sample stock returns are significantly leptokurtotic since they display negative skewness and large values of kurtosis.[1] The statistics for Jarque-Bera test suggest that the null hypothesis of normality should be rejected at the 5% level. Thus, sample stock returns show significantly departures from the normal distribution. Additionally, we employ the Ljung-Box test to check for serial correlation in the returns. We use lags equal to 5 and 10 because too small a lag may not capture serial correlation at high-order lags in this study (Ljung and Box 1979). Under the null hypothesis of no serial correlation, the test statistics are distributed asymptotically as a x^2 (chi-square) distribution with 5 and 10 degrees of freedom respectively. The Ljung-Box test statistics for 11 out of 52 stock returns do not reject the null hypothesis of no-serial correlation. The rest of individual stock returns including All Ord and ASX 50 indices show significant dependence between observations.

As argued by Klemes (1994), non-stationary in the mean tends to upwardly bias the estimated Hurst exponent. It is worth testing the stationarity of sample stock returns. The stationarity test used in this section included Augmented Dickey-Fuller (ADF) and Phillips-Peron (PP) tests. These tests can be estimated with or without an intercept and a trend term as well as for various lag lengths. The null hypothesis of the ADF and PP tests is that a time series contains a unit root, I (1) process against stationary as an alternative. For each of the ADF and PP tests, the 1% and 5% critical values are -3.96 and -3.41, respectively. Table 2

[1] Normally, a normal distribution is not skewed and is defined to have a coefficient of kurtosis of 3.

reports the results of stationary tests for all stock returns. The results of the ADF and PP tests for all sample returns, computing the statistics with and without trend, indicate that the null hypothesis is rejected at the 1% significance level. Thus all sample returns are stationary.

The assumption of market efficiency implies that financial events are independent and identically distributed. That is, stock returns fit a Gaussian (normal) distribution. However, subsequent studies found the probability distribution of the stock returns does not follow the Gaussian distribution. It is commonly observed that the distribution of stock returns have negative skewness and higher kurtosis than the normal distribution. Negative skewness means that more observations are shown in left-hand (negative) tail than in the right-hand (positive) tail. Thus the probability distribution of stock returns observed has fatter tails and higher peak than theoretical Gaussian distribution. The distribution is called a 'leptokurtosis'. One of the most common explanations for the fat-tailed distribution is that new information infrequently arrives at the financial markets. Theoretically, once the information arrives at markets, investors immediately react to information. However, in reality each investor has different trading horizons. For example, when new information arrives at the financial markets, some investors react immediately to new information, while others delay their reactions until confirming new information and wait until a trend is well shown up in the markets. Thus, the information is accumulated and suddenly reacted to. Thus, the fat-tailed distribution is created by heterogenous trading horizons.

To demonstrate fat-tailed distributions for stock returns, the distribution of stock returns can be described by simulating a Lorentz distribution.[2] Figure 2 displays the empirical distributions of all stock returns using the probability density function (PDF). While the dot line represents the Gaussian distribution, the solid line represents the Lorentz distribution which is characterised by the fat-tailed distribution. The distribution of the returns clearly reveals the fat-tailed distribution since round spots track the Lorentz distribution. Thus,

[2] $P(r) = f_0 + \frac{2b}{\pi}\frac{a}{r^2 + a^2}$

the returns are not independently and identically measured with the Gaussian random variances.

In summary, it can be seen that all stock returns show a non-normal distribution. It is widely accepted that the distribution of financial time series have fatter tails than the Gaussian distribution. Such fat-tailed distributions are normally attributed to long memory (Skjeltorp 2000). These finding suggest the inappropriateness of the normality assumption for modelling stock returns.

III. Empirical results

1. The results of R/S analysis

This section will be extended to include an examination of long memory and non-periodic cycles in daily stock returns using the rescaled ranges analysis. In general, high frequency data (daily or more frequent data) exhibit significant autoregressive (AR) processes. In the previous section, the statistics of Ljung-Box test suggest that there is linear dependence in all sample stock returns. To apply the R/S analysis method, it is necessary to remove and minimise the presence of linear dependence which can bias the Hurst exponent. The linear dependence may cause a significant long memory process when no long memory process exists. Peters (1994) suggested that such linear dependence can be pre-whitened by taking the first order auto-regressive AR (1) residuals to minimize the bias.

As the first step in the R/S analysis, we considered the residual of the AR (1) model proposed by Peters (1994). From equation (1), R_t is regressed as the dependent variable against the independent variable R_{t-1}. By taking the regression, we obtain the intercept coefficient, a, and slope coefficient, b. Then the AR (1) residual of R_t subtracts out the dependence of R_t on R_{t-1},

$$X_t = R_t - \left(a + b \cdot R_{t-1}\right) \qquad (2)$$

where X_t is the AR (1) residual of S at time t. Peters (1994) suggested another rule of thumb with regard to the financial data when doing R/S analysis. Practically, when doing the regression, a minimum starting point is allowed to be $n \geq 10$. The reason for this is that values of $n < 10$ produces unstable estimates when sample sizes are small.

To examine the evidence of long memory and non-periodic cycle, the first step of the R/S analysis divides the sample into sub-periods of equal length n. The data may be divided by 29 divisors which is greater or equal to 10: 10, 12, 15 17, 20, $\ldots$, 2550. The next step is to calculate the estimated R/S values and do regression on the log-log plot of R/S values against the sub-period length n. Table 3 shows the results of the rescaled range analysis for the daily All Ords returns. The log-log plot of the empirical R/S values (R/S) for the daily All Ord returns is presented in Figure 3. Also plotted are the expected R/S (E(R/S)) values as a comparison against the null hypothesis that the system is an independent process. In general, the R/S plot displays the same pattern as the E(R/S) plot until $n = 425$ days or log (n) = 2.628. This means that the R/S value series follow a random walk. However, where $n > 425$, there is clearly a systematic deviation between the R/S and the E(R/S) plots. Two obvious different points in the plot of the R/S appear at 850 days and at 1700 days. After 1700 days, the slope declines, and the trend reverses.

The V-statistic against log (n) is to examine the deviation between the R/S and the E(R/S) values for the daily All Ordinaries index returns. Figure 4 shows that the ratio of V-statistic for the R/S vales is increasing at a faster rate than that of V-statistic for the E(R/S) values. The potential multiple cycles within this data as a number of break points appear at $n = 204$ (roughly 10 months), at $n = 850$ (roughly 3.4 years) and $n = 1700$ (roughly 6.7 years).[3] Up to the 204 days, the slope of V-statistic for the empirical R/S in this region looks the same as that of V-statistic for the expected R/S. The slope increases dramatically between 300 days and 850 days as well as between 1020 days and 1700 days.

[3] These cycles are estimated based on a 252-working-day year.

Table 4 displays the empirical Hurst exponent (H) and the expected Hurst exponent $(E(H))$ estimated with each of sub-periods visually identified in Figure 4.8. In the longer period $102 \le n \le 1700$, the empirical H is 0.563 and the estimated $E(H)$ is 0.526. Additionally, the significance test suggests that the estimated H value is roughly 2.60 standard deviations away form its expected value, and is highly significant. This implies that this series is persistent and have the average non- periodic cycle of approximately 6.7 years. The third and forth columns of Table 4 show regression results for the sub-period $102 \le n \le 204$, the H is found to be 0.563 while the $E(H)$ is 0.546. Nevertheless, as indicated by the significance test, the estimated H value is only 1.22 standard deviations away form its expected value and is statistically insignificant. Therefore, it appears that the returns in this sub-period do not posses long memory and non-periodic cycles. Finally, columns 5 to 8 present regression results for the sub-period $300 \le n \le 850$ and $1220 \le n \le 1700$ respectively. In both cases, the empirical H values are highly significant results which indicate that long memory and non-periodic cycles exist in the returns, i.e. approximately 3.4-year and 6.7-year cycles. As a result, the results clearly suggest that the return series for the daily All Ordinaries index show long memory and two non-periodic cycles. One is an approximately 3.4-year cycle and another is an approximately 6.7-year cycle. This finding is consistent with McKenzie (2001) who found approximately 3 and 6 year non-periodic cycles in the daily All Ordinaries index returns over period 1980-1998. McKenzie further noted that these cycles are consistent with business cycles.

2. Results of fractionally differencing test

In preceding sections, we examine the presence of long memory and non-periodic cycles in the Australian stock market using the rescaled range analysis. This section investigates the presence of long memory in the daily ASX 50 index and its 50 constituents using the ARFIMA model. The most common weakness of the rescaled range analysis is the sensitivity of short-term dependence. To overcome this problem, the GPH test is used in this section to examine the null hypothesis of a short memory process against long memory. The GPH test is the most widely used method to calculate the long memory parameter d without the autoregressive and moving average parameters.

However, the use of the GPH test has a severe limitation due to its poor finite sample size. A choice has to be made with respect to the number of low-frequency ordinates, ν in the estimation. Inclusion of medium or high order periodogram ordinates will cause bias in the d estimate. Cheung and Lai (1993b, p. 107) argued that 'a too small value of ν will lead to imprecise estimates due to limited degrees of freedom in the regression'. In order to ensure the robustness of the GPH test to the choice of the number of low-frequency ordinates, this paper follows the work of Barkoulas et al. (2000) which allows several choices of low-frequency ordinates. These choices vary with the sample size T and are established in terms of $\nu = T^{\alpha}$ with α = {0.5, 0.525, 0.55, 0.575, and 0.6}. Table 5 shows the d estimates corresponding to $d(0.50)$, $d(0.525)$, $d(0.55)$, $d(0.575)$ and $d(0.60)$ when sample size $\nu = T^{0.50}, T^{0.525}, T^{0.55}, T^{0.575}$ and $T^{0.60}$ respectively. To test for the significance of the d estimates, the null hypothesis ($H_0 : d = 0$) and the alternative ($H_0 : d \neq 0$) are established.

Table 5 reports estimates of the fractional differencing parameter (d) for the daily ASX 50 index and its constituent stocks. The d estimates are provided with *t*-statistics. The value of d estimate for the daily ASX 50 index is less than 0.5, which shows anti-persistence. However, each individual stock returns show different values of d estimates which can be interpreted as follows:

1. Significant evidence of persistence ($d > 0$) exists in only five stock returns (BIL, CSL, PBL, TEL and WPL). These individual stock returns show positive evidence of long memory. This implies that if the prices have been up (down) in the last period, they will continue to be up (down) in the next period.

2. Significant evidence of anti-persistence ($d < 0$) can be found in ten stock returns (GPT, NAB, NCM, QBE, RIO, SGP, STO, SUN, WDC and WBC). This indicates that whenever time series have been up (down) in the last period, they are likely to be down (up) in the next period.
3. For the rest of individual stock returns the null hypothesis ($H_0 : d = 0$) can not be rejected which implies that these returns have short memory with the stationary and invertible ARMA process.

In summary, we find that the daily ASX 50 index shows an anti-persistent process which is representative of only 25% of the stocks comprising the individual stock shares. Five individual stock returns show significant evidence of long memory while the majority of stock returns is found to display no evidence of long memory. Therefore, it can be concluded that the market index is not representative of all market characteristics and evidence of long memory from an index return does not necessarily holds at the individual company level.

IV. Conclusion

The aim of this study is to re-examine the evidence of long memory in the Australian equity market. Our results indicate that the returns on the All Ords display persistence with two non-period cycles with lengths of approximately 3.4 and 6.7 years. Additionally, we find that although there is evidence of anti-persistence for the ASX 50 index, this result does not hold at the individual stock level as only 25% of individual stocks appear to follow an anti-persistence process while the majority of the stocks show an absence of long memory.

References

Agiaklogou, C, Newbold, P and Wohar, M (1992): "Bias in an estimator of the fractional difference parameter", *Journal of Time Series Analysis*, 14, 235-246.

Barkoulas, J T, Baum, C F and Travlos, N (2000): "Long Memory in the Greek Stock Market", *Applied Financial Economics*, 10, 177-184.

Cajueiro, D O and Tabak, B M (2004): "Evidence of long range dependence in Asian equity markets: the role of liquidity and market restrictions", *Physica A*, 342, 656-664.

Cheung, Y W and Lai, K S (1995): "A search for long memory in international stock market returns", *Journal of International Money and Finance*, 14(4), 597-615.

Granger, C W J and Joyeux, R (1980): "An Introduction to Long Memory Time Series Models and Fractional Differencing", *Journal of Time Series Analysis*, 1, 5-39.

Geweke, J and Porter-Hudak, S (1983): "The Estimation and Application of Long Memory Time Series Models", *Journal of Time Series Analysis*, 4, 221-238.

Henry, O T (2002): "Long Memory in Stock Returns: Some International Evidence", *Applied Financial Economics*, 12(10), 725-729.

Howe, J S, Martin, D W and Wood, B G (1999): "Much Ado about Nothing: Long-term Memory in Pacific Rim Equity Markets", *International Review of Financial Analysis*, 8(2), 139-151.

Hosking, J R M (1981): "Fractional Differencing", *Biometrika*, 68(1), 165-176.

Klemes, V (1974): "The Hurst Phenomenon: A Puzzle?", *Water Resources Research*, 10(4), pp. 675-687.

Lo, A W (1991): "Long-Term Memory in Stock Market Volatility", *Journal of Econometrica*, 59(5), 1279-1313.

Ljung, G and Box, G (1979): "On a Measure of Lack of Fit in Time Series Models", *Biometrika*, 66, 265-270.

McKenzie, M D (2001): "Non-periodic Australian Stock Market Cycles: Evidence from Rescaled Range Analysis", *The Economic Record*, 77(239), 393-406.

Mills, T C (1993): "Is There Long-Term Memory in UK stock returns?", *Applied Financial Economics*, 3, 303-306.

Peters, E E (1994): *Fractal Market Analysis: Applying Chaos Theory to Investment and Economics*, John Wiley & Sons, New York

Skjeltorp, J A (2000): "Scaling in the Norwegian stock market", *Physica A*, 283(3-4), 486-528.

Tolvi, J (2003): "Long memory and outliers in stock market returns", *Applied Financial Economics*, 13, 495-502.

Figure 1. Daily closing prices of the ALL Ordinaries index for the period 1984 to 2005

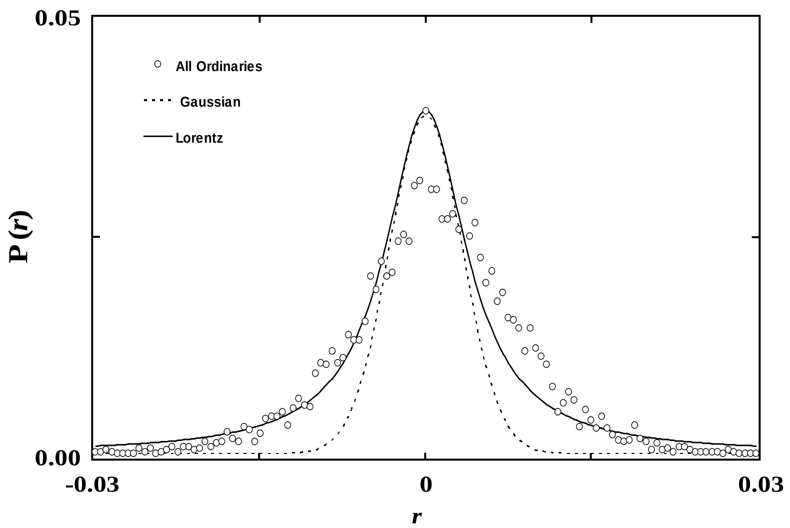

Figure 2. Probability Density Function $P(r) = \frac{2b}{\pi}\frac{a}{r^2 + a^2}$ **of the daily All Ordinaries index**

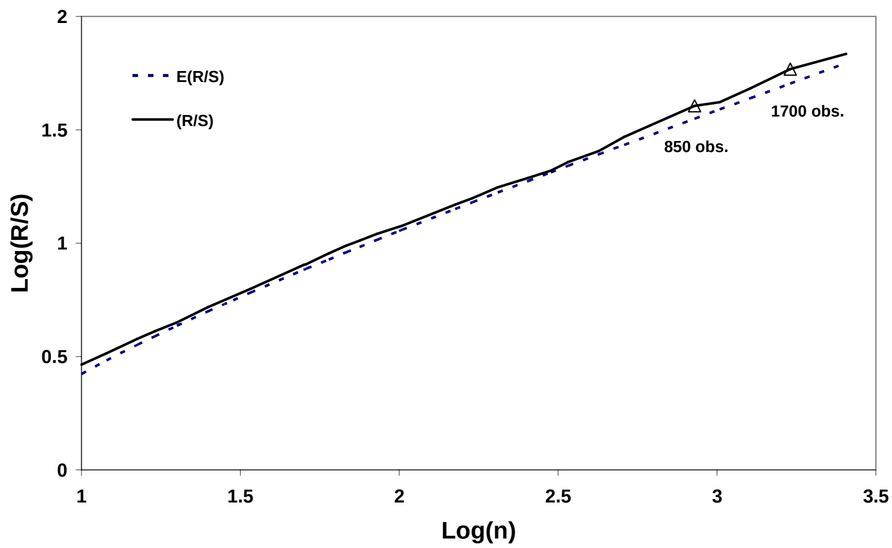

Figure 3. The log-log plot of the empirical R/S (R/S) and the expected R/S (E(R/S)) for the daily All Ordinaries index.

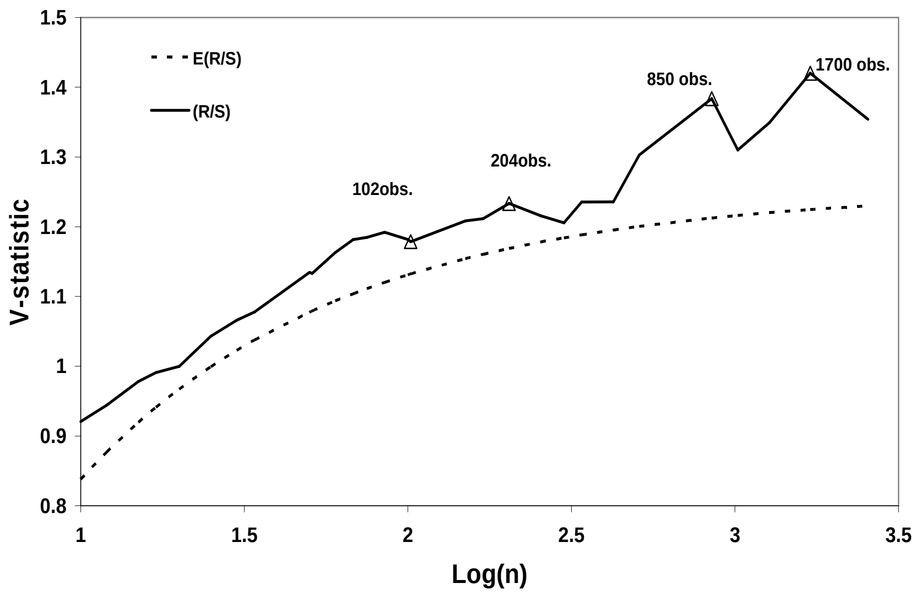

Figure 4. The V-statistic for the empirical R/S (R/S) and the expected R/S (E(R/S)) against log (n)

Table 1. Summary statistics for all stock returns

Symbol	Mean	SD	Skew	Kurt	J-B	Q(5)	Q(10)
				Market indices			
All Ords	0.0338	0.01	-6.22	179.04	6723742**	83.32**	116.62**
ASX 50	0.0003	0.011	-5.23	152.10	55229757**	97.14**	127.00**
				Individual stock indices			
AGL	0.0002	0.020	-7.36	255.07	16029531**	40.89**	46.78**
AMC	0.0002	0.016	-3.73	91.35	1920466**	34.34**	78.52**
AMP	-0.0007	0.022	-1.96	41.05	104277.5**	6.586	11.27
ANZ	0.0002	0.017	-4.09	95.30	218684.2**	39.34**	44.43**
AWC	0.0000	0.229	-4.64	107.37	2797835**	33.88**	34.94**
AXA	0.0004	0.020	0.50	8.20	2500.898**	11.43**	17.06
BHP	0.0000	0.021	-13.93	465.05	54665293**	8.297	13.03
BIL	0.0002	0.025	-31.09	1721.2	752000000**	7.597	11.07
BLD	0.0007	0.016	-0.87	14.34	7030.656**	9.21	12.28
BSL	0.0016	0.017	-0.31	4.16	49.529**	13.22**	17.61
CBA	0.0005	0.012	-0.42	7.45	2934.033**	29.85**	32.50**
CCL	0.0002	0.022	-8.46	223.76	12429566**	14.41**	20.37**
CML	0.0002	0.018	16.25	715.15	129000000**	4.68	7.63
CSL	0.0010	0.020	1.44	24.87	55414.95**	32.14**	36.91**
CSR	-0.0002	0.025	-28.32	1567.0	625000000**	8.89	12.35
FGL	0.0001	0.022	-2.00	119.47	3423093**	35.64**	55.28**
FXJ	0.0003	0.016	-0.03	5.63	942.22**	58.11**	58.79**
GPT	0.0001	0.013	-2.27	63.15	898080.3**	38.12**	46.77**
IAG	0.0006	0.017	-1.09	17.41	10324.3**	15.24**	23.95**
JHX	0.0001	0.018	-0.47	8.81	1207.838**	11.04	22.82**
LLC	0.0002	0.019	-11.08	379.72	35994611**	24.43**	35.45**
MAY	0.0005	0.019	-2.67	62.52	879301.6**	39.45**	49.20**
MBL	0.0009	0.016	-1.29	28.52	51006.3**	28.34**	41.63**
MGR	0.0002	0.009	-0.07	4.14	80.55**	12.69**	14.49
MIG	0.0005	0.018	0.16	11.19	5823.66**	11.53**	22.02**
NAB	0.0004	0.015	-1.32	26.58	143451.1**	9.08	20.76**
NCM	0.0004	0.036	14.60	607.53	68607513**	2.68	9.22
NWS	0.0004	0.035	-12.24	501.30	59592566**	19.21	20.76**
NWSLV	0.0006	0.028	7.29	192.64	3951026**	4.44	6.79
ORG	0.0001	0.019	-1.76	26.72	146497.8**	8.24	20.04**
ORI	0.0003	0.017	-1.15	25.17	126239.2**	29.28**	32.99**
PBL	0.0006	0.039	16.92	696.43	89611639**	40.59**	43.01**
PMN	0.0019	0.015	0.11	5.48	124.13**	28.27**	30.26**
QAN	-0.0002	0.021	0.45	22.77	22055.93**	12.85**	17.76
QBE	0.0003	0.027	-0.97	275.26	16262534**	125.12**	141.4**
RIN	0.0016	0.015	0.53	4.57	75.62**	12.82**	22.18**
RIO	0.0003	0.019	-1.37	35.15	265536**	62.94**	66.44**
SGB	0.0004	0.012	-0.13	9.44	5582.61**	10.90	12.47
SGP	0.0003	0.013	-1.30	36.44	264940.3**	44.77**	66.13**
STO	-0.0001	0.023	-18.85	904.16	207000000**	22.31**	28.07**
SUN	0.0006	0.015	-0.50	13.55	19772.19**	7.71	13.23
TAH	0.0008	0.014	0.10	4.54	271.55**	15.97**	22.88**
TEL	0.0005	0.020	0.93	18.67	25091.09**	11.71**	24.79**
TLS	0.0003	0.016	3.57	73.71	390237.4**	12.73**	24.61**
WBC	0.0003	0.015	-1.52	25.96	136828.9**	52.25**	77.10**
WDC	0.0005	0.258	0.00	56.15	133203.8**	180.6**	218.8**
WES	0.0006	0.020	-9.30	318.48	20891451**	24.84**	25.45**
WMR	0.0012	0.028	3.09	54.29	64519.82**	10.46	11.30

WOW	0.0006	0.014	0.03	6.81	1792.83**	22.41**	31.70**
WPL	0.0003	0.022	-0.77	35.16	264234.2**	80.77**	84.94**

Note: Under the null hypothesis for normality, the Jarque-Bera statistic is distributed as $x^2(2)$. In the columns for $Q(n)$, the Ljung-Box statistic for returns up to n-th order of serial correlation. Critical values are 11.1 and 18.3 for n=5 and 10, respectively, at 5% significance. ** indicates significance at the 5% level.

Table 2. Stationary test for all stock returns

Symbol	**ADF**		**PP**	
	Without trend	With trend	Without trend	With trend
		Market indices		
All Ord	-24.580	-24.580	-68.070	-68.060
ASX 50	-31.428	-31.433	-70.238	-70.236
		Individual stock indices		
AGL	-35.953	-35.963	-72.226	-72.228
AMC	-34.521	-34.535	-74.940	-74.945
AMP	-18.426	-18.420	-39.610	-39.598
ANZ	-35.583	-35.603	-73.831	-73.840
AWC	-35.073	-35.070	-73.537	-73.531
AXA	-22.009	-22.005	-48.875	-46.863
BHP	-34.781	-34.787	-76.296	-76.297
BIL	-35.738	-35.763	-75.870	-75.884
BLD	-16.164	-16.160	-36.983	-36.969
BSL	-12.534	-12.524	-24.534	-24.518
CBA	-25.975	-25.977	-53.359	-53.354
CCL	-35.124	-35.131	-76.109	-76.111
CML	-35.338	-35.340	-76.937	-76.935
CSL	-24.893	-24.921	-47.911	-47.919
CSR	-36.299	-36.296	-78.174	-78.167
FGL	-35.362	-35.367	-75.933	-75.932
FXJ	-27.472	-27.488	-53.987	-53.998
GPT	-37.782	-37.778	-82.000	-81.993
IAG	-15.500	-15.552	-33.909	-33.934
JHX	-12.499	-12.534	-27.068	-27.077
LLC	-35.378	-35.403	-74.113	-74.124
MAY	-36.219	-36.231	-75.430	-75.435
MBL	-21.525	-21.541	-42.743	-42.750
MGR	-18.171	-18.176	-37.655	-37.650
MIG	-21.627	-21.623	-45.786	-45.774
NAB	-35.255	-35.254	-76.664	-76.659
NCM	-29.663	-29.686	-65.868	-65.878
NWS	-33.027	-33.032	-71.942	-71.940
NWSLV	-23.276	-23.273	-50.430	-50.421
ORG	-36.219	-36.232	-77.707	-77.713
ORI	-35.117	-35.119	-74.590	-74.587
PBL	-29.510	-29.508	-72.673	-72.667
PMN	-10.526	-10.668	-18.812	-18.899
QAN	-17.309	-17.318	-36.817	-36.814
QBE	-35.816	-35.812	-75.593	-75.586
RIN	-11.158	-11.141	-21.730	-21.707
RIO	-33.743	-33.744	-70.953	-70.950
SGB	-26.469	-26.479	-54.724	-54.726

SGP	-35.357	-35.358	-80.561	-80.558
STO	-34.830	-34.878	-74.095	-74.121
SUN	-30.365	-30.362	-64.393	-64.386
TAH	-25.060	-25.103	-51.250	51.287
TEL	-23.437	-23.500	-49.278	-49.323
TLS	-19.207	-19.207	-40.717	-40.797
WBC	-33.448	-33.451	-72.263	-72.260
WDC	-19.665	-19.647	-60.514	-60.482
WES	-30.796	-30.793	-74.947	-74.940
WMR	-12.127	-12.162	-27.628	-27.660
WOW	-27.064	-27.072	-56.787	-56.790
WPL	-36.290	-36.336	-75.504	-75,536

Note: The ADF and PP critical values without trend: -3.43 and -2.86 at the 1% and 5% significance levels, respectively; the ADF and PP critical values with trend: -3.97 and -3.41 at the 1% and 5% significance levels, respectively.

Table 3. The results of the rescaled range analysis for the daily All Ordinaries Index

N	Log(n)	Log(R/S)	Log(E(R/S))	V-statistic R/S	V-statistic E(R/S)
10	1.0000	0.4642	0.4233	0.9208	0.8381
12	1.0792	0.5146	0.4825	0.9440	0.8768
15	1.1761	0.5784	0.5515	0.9781	0.9193
17	1.2304	0.6112	0.5888	0.9908	0.9410
20	1.3010	0.6505	0.6360	0.9999	0.9670
25	1.3979	0.7173	0.6986	1.0431	0.9992
30	1.4771	0.7662	0.7483	1.0658	1.0227
34	1.5315	0.7984	0.7818	1.0780	1.0376
50	1.6990	0.9042	0.8819	1.1344	1.0774
51	1.7076	0.9081	0.8869	1.1332	1.0792
60	1.7782	0.9547	0.9279	1.1631	1.0935
68	1.8325	0.9887	0.9591	1.1816	1.1037
75	1.8751	1.0112	0.9833	1.1849	1.1112
85	1.9294	1.0410	1.0140	1.1921	1.1202
100	2.0000	1.0726	1.0535	1.1818	1.1310
102	2.0086	1.0756	1.0583	1.1785	1.1323
150	2.1761	1.1703	1.1504	1.2084	1.1543
170	2.2304	1.1985	1.1799	1.2114	1.1605
204	2.3096	1.2459	1.2226	1.2333	1.1688
255	2.4065	1.2881	1.2744	1.2157	1.1780
300	2.4771	1.3198	1.3119	1.2056	1.1840
340	2.5315	1.3575	1.3407	1.2353	1.1884
425	2.6284	1.4061	1.3917	1.2357	1.1954
510	2.7076	1.4688	1.4332	1.3031	1.2005
850	2.9294	1.6057	1.5484	1.3836	1.2126
1020	3.0086	1.6216	1.5893	1.3100	1.2162
1275	3.1055	1.6828	1.6392	1.3491	1.2202
1700	3.2304	1.7676	1.7033	1.4202	1.2247
2550	3.4065	1.8349	1.7932	1.3540	1.2300

Table 4. Regression results from the R/S analysis

	$102 \le n \le 1700$		$102 \le n \le 204$		$300 \le n \le 850$		$1220 \le n \le 1700$	
	R/S	**E(R/S)**	**R/S**	**E(R/S)**	**R/S**	**E(R/S)**	**R/S**	**E(R/S)**
Constant (SE)	-0.0598 (0.0202)	0.0059 (0.0005)	-0.0552 (0.0150)	-0.0388 (0.0042)	-0.2470 (0.00449)	0.0174 (0.0030)	-0.3622 (0.0413)	0.0433 (0.0016)
No of points	13	13	4	4	5	5	3	3
DOF	11	11	2	2	3	3	1	1
Adj. R Squared	0.9977	0.9998	0.9995	0.9999	0.9976	0.9999	0.9991	0.9999
Hurst exponent SE	0.5630 (0.0148)	0.5264 (0.0018)	0.5629 (0.0068)	0.5463 (0.0019)	0.6323 (0.0169)	0.5227 (0.0001)	0.6599 (0.0133)	0.5135 (0.0005)
Significance test	2.5985		1.2237		7.8892		10.4360	

Table 5. Estimates of the fractional differencing parameter (d)

Data	$d(0.50)$	$d(0.525)$	$d(0.55)$	$d(0.575)$	$d(0.60)$
S&P / ASX 50	-0.105 (-1.42)	-0.129 (-1.80)*	-0.123 (-2.29)**	-0.047 (-0.91)	-0.005 (-0.104)
AGL	0.011 (0.13)	0.092 (1.19)	0.050 (0.75)	0.004 (0.06)	-0.029 (-0.59)
AMC	0.013 (0.16)	-0.050 (-0.61)	-0.023 (-0.35)	-0.018 (-0.30)	-0.044 (-0.86)
AMP	0.009 (0.11)	0.111 (1.24)	0.056 (0.68)	0.046 (0.65)	-0.005 (-0.08)
ANZ	-0.038 (-0.47)	-0.039 (-0.58)	-0.043 (-0.72)	-0.058 (-1.13)	-0.029 (-0.63)
AWC	-0.096 (-1.24)	-0.077 (-1.11)	-0.095 (-1.51)	-0.034 (-0.61)	0.002 (0.05)
AXA	-0.091 (-1.03)	-0.09 (-1.18)	-0.005 (-0.06)	-0.006 (-0.08)	-0.061 (-0.89)
BHP	-0.056 (-0.72)	-0.058 (-0.84)	-0.046 (-0.76)	-0.022 (-0.43)	-0.014 (-0.31)
BIL	0.083 (1.39)	0.129 (2.06)**	0.056 (1.05)	0.088 (1.71)*	0.060 (1.33)
BLD	0.087 (0.72)	0.004 (0.04)	-0.007 (-0.07)	-0.011 (-0.12)	-0.054 (-0.71)
BSL	0.094 (0.84)	0.118 (1.15)	0.148 (1.40)	0.141 (1.46)	0.140 (1.62)
CBA	-0.064 (-0.79)	-0.085 (-1.16)	-0.051 (-0.73)	-0.014 (-0.22)	0.012 (0.21)
CCL	-0.008 (-0.13)	0.060 (1.00)	0.107 (1.57)	0.074 (1.25)	0.062 (1.22)
CML	0.001 (0.01)	0.024 (0.30)	0.012 (0.17)	0.009 (0.15)	0.038 (0.72)
CSL	0.129 (1.34)	0.17 (2.06)**	0.18 (2.48)**	0.100 (1.46)	0.076 (1.24)
CSR	0.027 (0.36)	0.005 (0.08)	-0.050 (-0.85)	-0.002 (-0.03)	-0.023 (-0.47)
FGL	0.024 (0.29)	0.005 (0.07)	-0.032 (-0.51)	-0.062 (-1.12)	-0.072 (-1.49)
FXJ	0.052 (0.44)	0.064 (0.63)	-0.021 (-0.24)	-0.017 (-0.21)	-0.041 (-0.63)
GPT	-0.121 (-1.20)	-0.180 (-2.04)**	-0.173 (-2.25)**	-0.182 (-2.84)***	-0.173 (-3.12)***
IAG	0.023 (0.21)	0.013 (0.12)	-0.073 (-0.77)	-0.038 (-0.44)	-0.101 (-1.35)
JHX	-0.126 (-0.96)	-0.166 (-1.43)	-0.102 (-0.93)	-0.135 (-1.39)	-0.127 (-1.45)
LLC	-0.094 (-1.21)	-0.055 (-0.79)	-0.021 (-0.33)	-0.035 (-0.63)	-0.058 (-1.18)
MAY	-0.067 (-0.84)	-0.011 (-0.13)	0.006 (0.08)	-0.007 (-0.11)	-0.028 (-0.52)
MBL	0.094 (0.84)	0.126 (1.32)	0.106 (1.32)	0.041 (0.55)	-0.001 (-0.01)
MGR	-0.150 (-1.08)	-0.135 (-1.12)	-0.158 (-1.48)	-0.094 (-0.96)	-0.121 (-1.33)
MIG	0.137 (1.37)	0.116 (1.23)	0.078 (0.98)	0.048 (0.68)	0.055 (0.83)
NAB	-0.097 (-1.40)	-0.119 (-2.00)**	-0.148 (-2.73)***	-0.144 (-3.02)***	-0.114 (-2.70)***
NCM	-0.119	-0.158	-0.164	-0.148	-0.115

	(-1.17)	(-1.86)*	(-2.26)***	(-2.37)**	(-2.12)**
NWS	-0.016 (-0.25)	0.016 (0.27)	-0.019 (-0.37)	0.020 (0.43)	0.012 (0.29)
NWSLV	-0.019 (-0.16)	-0.044 (-0.46)	-0.028 (-0.33)	0.034 (0.38)	-0.001 (-0.01)
ORG	0.035 (0.43)	0.009 (0.13)	0.006 (0.10)	-0.011 (-0.21)	-0.014 (-0.29)
ORI	0.016 (0.20)	-0.021 (-0.30)	0.002 (0.04)	-0.026 (-0.49)	-0.046 (-1.00)
PBL	0.047 (0.67)	0.028 (0.44)	0.047 (0.81)	0.044 (0.90)	0.082 (1.66)*
PMN	-0.063 (-0.44)	-0.058 (-0.46)	-0.064 (-0.56)	0.012 (0.12)	0.009 (0.10)
QAN	-0.013 (-0.10)	0.063 (0.46)	-0.025 (-0.20)	-0.048 (-0.47)	-0.043 (-0.48)
QBE	-0.133 (-1.73)*	-0.127 (-1.92)*	-0.166 (-2.96)***	-0.136 (-2.66)***	-0.126 (-2.76)***
RIN	-0.074 (-0.46)	-0.083 (-0.59)	0.003 (0.023)	-0.060 (-0.49)	-0.088 (-0.80)
RIO	-0.149 (-2.37)**	-0.133 (-2.37)**	-0.166 (-3.36)***	-0.078 (-1.54)	-0.058 (-1.25)
SGB	-0.079 (-0.97)	-0.011 (-0.14)	-0.016 (-0.23)	-0.015 (-0.25)	-0.039 (-0.75)
SGP	-0.131 (-1.85)*	-0.138 (-2.22)**	-0.097 (-1.81)*	-0.088 (-1.83)*	-0.087 (-1.99)**
STO	-0.115 (-1.75)*	-0.116 (-2.04)**	-0.069 (-1.22)	-0.089 (-1.80)*	-0.083 (-1.99)**
SUN	-0.133 (-1.61)	-0.155 (-2.21)**	-0.131 (-1.98)**	-0.108 (-1.84)*	-0.073 (-1.37)
TAH	0.131 (1.26)	0.088 (0.94)	0.030 (0.37)	-0.054 (-0.72)	-0.037 (-0.57)
TEL	0.171 (1.60)	0.187 (1.97)**	0.109 (1.32)	0.076 (1.08)	0.088 (1.37)
TLS	0.209 (1.41)	0.161 (1.28)	0.087 (0.80)	0.013 (0.14)	-0.031 (-0.37)
WBC	-0.109 (-1.51)	-0.079 (-1.04)	-0.129 (-2.03)**	-0.14 (-2.60)***	-0.120 (-2.52)**
WDC	-0.168 (-1.98)**	-0.182 (-2.50)**	-0.129 (-1.99)**	-0.052 (-0.90)	-0.012 (-0.22)
WES	0.026 (0.38)	0.081 (1.20)	0.081 (1.32)	0.081 (1.41)	0.028 (0.55)
WMR	-0.093 (-0.40)	-0.168 (-0.80)	-0.182 (-1.02)	-0.235 (-1.50)	-0.180 (-1.32)
WOW	0.079 (0.87)	0.096 (1.13)	0.023 (0.30)	0.050 (0.75)	0.016 (0.27)
WPL	0.060 (0.78)	0.089 (1.33)	0.115 (1.91)*	0.096 (1.78)*	0.101 (2.17)**

*** Implies rejection of the null of the two-sided test at the 1% level.
** Implies rejection of the null of the two-sided test at the 5% level.
* Implies rejection of the null of the two-sided test at the 10% level.

Two-sided test $H_0 : d = 0$ and $H_1 : d \neq 0$

Two-sided critical values: 2.576(1%), 1.960(5%), and 1.645 (10%)