TESTING FOR EFFICIENCY IN THE THE PRESENCE OF INFREQUENT TRADING- THE BOMBAY STOCK INDEX

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Abstract

Most tests of weak form efficiency of stock market prices are conducted on aggregate stock indices. Aggregation however introduces measurement biases when the constituent stocks in the index do not trade frequently. Non synchronous lagged trading and the consequent catching up, is likely to show up as spurious autocorrelation, rendering imprecise the inferences drawn from tests of market efficiency. We conjecture that the failure to correct for infrequent trading may account for the market inefficiency often reported in the extant literature on thinly traded emerging markets. As the observed index may not represent the true underlying index value in these markets, there is a systematic bias toward rejecting the efficient market hypothesis. This paper tests the random walk hypothesis for the Bombay Sensitive Stock Index (Sensex), the oldest stock exchange index in Asia. The tests are first conducted on the observed index and then replicated using the estimated true index corrected for infrequent trading. The observed index is corrected for infrequent trading using the Beveridge and Nelson (1981) decomposition. The observed index exhibits significant deviations from a random walk, in marked contrast, the corrected index is weak form efficient. Separating out the effects of infrequent trading reduces the likelihood of spurious rejections of the RWH. and weak form efficiency.

Keywords: infrequent trading, random walk, market efficiency, emerging markets, Bombay equity markets.

JEL Classification: G12/G14/G22

1. Introduction

With profound implications for investors, investment strategies, funds management, and for financial markets, the Efficient Market Theory and the Random Walk Thesis has been extensively tested for numerous developed and emerging markets. Survey of efficient market studies by Fama (1970) provides overwhelming evidence to support the efficient market hypothesis for U.S. stock markets. In recent years, however, numerous departures from market efficiency in the form of anomalies have attracted the attention of academics and practitioners alike. Evidence against the random walk hypothesis (RWH) for stock returns in the developed capital markets are reported by Fama and French (1988), Lo and MacKinlay (1988) among others. Fama (1998) maintains that most return anomalies in the major stock markets are chance results that tend to disappear in the long-term with a reasonable change in methodology, hence supporting the view that mature capital markets are generally efficient.
Increasing globalization of the financial markets and the seamless nature of cross border investment flows has heightened interest in emerging markets. Several studies have focused

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on predictability of return in the less mature emerging markets. Urrutia (1995) using the variance-ratio test rejects the RWH for the Latin American emerging equity markets of Argentina, Brazil, Chile, and Mexico, while the runs test indicate weak form efficiency. In contrast, Ojah and Karemera (1999) find that the Latin American equity returns follow a random walk and are generally weak-form efficient. Grieb and Reyes (1999) reexamine the random walk properties of stocks traded in Brazil and Mexico using the variance ratio tests and conclude that index returns in Mexico exhibit mean reversion and a tendency towards random walk in Brazil. These conflicting inferences may perhaps be attributable to the effect of cross sectional and temporal variations in the degree of infrequent trading in these emerging markets.

Using the variance ratio test and the runs test for the period 1990 to 1999, this paper examines the random walk properties of the Indian equity market as measured by the value weighted index of 30 bell weather stocks that trade on the Bombay Stock Exchange (BSE) - the oldest stock exchange in Asia,. A major difficulty in interpreting the results from tests on thinly traded markets, is the confounding effect of infrequent trading on the observed index. Thus, rejection of the RWH or the efficient markets hypothesis could simply be a result of having used the observed index - an imprecise estimate of the true value of the index in the presence of non synchronous trading. Infrequent trading is widespread in most emerging markets and is particularly so in the case of the market under examination here. In 1994 a competing stock exchange – the National Stock Exchange (NSE) began operating in India, bringing with it a number of reforms and improvement in the quality of trading. Nevertheless, the market still suffers from poor liquidity, high bid-ask spreads, relatively low transparency, and as seen in the recent past has been subjected to a number of cases of price manipulation. Pandey (2002) using an ARMA specification augmented with monthly dummies shows that the Bombay sensitive index exhibits marked monthly seasonality.

A number of different approaches have been suggested to correct for infrequent trading. Stoll and Whaley (1990) use the residuals from an ARMA(p,q) regression as a proxy for the true index, while Bassett, France, and Pliska (1991) propose the use of a Kalman filter to estimate the distribution of the true index. In this paper we employ a modified version of the Stoll and Whaley approach suggested by Jokivuolle (1995), to estimate the true unobservable index from the history of the observed index. The correction consists of decomposing the log of the observed index into its random and stationary components using the Beveridge and Nelson (1981) methodology, where the random component can be shown to equal the log of the true index. Separating the effects of infrequent trading, allows us to draw definitive conclusions regarding market efficiency and random walks. For the market studied in this paper, the apparent weak form inefficiency observed can almost entirely be attributed to infrequent trading, and disappears when one uses the estimated true index corrected for infrequent trading.

The remainder of this paper proceeds as follows. Section 2 provides an overview of the Bombay stock market. Analytical details of the Beveridge and Nelson decomposition to estimate the true index, and the test methodology for assessing the RWH are described in Section 3. Section 4 identifies the data sources, presents the empirical results, and contrasts the findings between the observed and the corrected indices. Section 5 concludes.

2. Overview of the Bombay Equity Markets

The Bombay Stock Exchange, which started in 1875 as "The Native Share and Stockbrokers Association" is the oldest exchange in Asia, predating the Tokyo Stock Exchange by 3 years. For the better part of its existence it held a preeminent position as a monopolistic institution for security trading in India. More recently its position has been challenged by the National Stock Exchange (NSE) an online electronic exchange which was established in 1994. It is therefore not surprising that this monopolistic position of the BSE has led to dubious practices, resulting in lack of transparency, high transaction costs and poor liquidity.

Over 7000 stocks are listed at the BSE, (of these, about 1300 are cross listed at the newly formed NSE). Whereas, almost 100% of trading used to take place at the BSE, its share has fallen to about 35% in recent years. There is no organized source of price data for all the securities that trade on the BSE. What is collected and disseminated by the BSE is a 30 stock index called the Bombay Sensitive Index, popularly referred to as the Sensex. The stocks included in the Sensex account for about 38% to 40% of the capitalization of all stocks listed at the exchange.

Along with overall financial reforms in the Indian financial sector, the BSE also has undergone some changes in recent years, notably the introduction of its online trading system (BOLT), presumably aimed at dealing with the increased competition from the newcomer on the block – the NSE. The total market capitalization of the BSE market is estimated at 3.8 trillion Indian rupees (approximately US$ 82), about 38% of which is represented by the 30 stocks of the Sensex.

3. Methodology

a. Variance Ratio Test for Random Walk.

A consequence of informational efficiency is that asset returns should manifest properties of a random walk. An important property of the random walk process is that the variance of the increments to the random walk process linearly increase with the sampling interval. Lo and MacKinlay (1988) proposed a simple specification test for evaluating the random walk properties of asset prices. Specifically if X_t is a pure random walk, the ratio of the variance of the q^{th} difference scaled by q, to the variance of the first difference must approach unity. The variance ratio VR(q) is defined as:

$$VR(q) = \frac{\sigma^2(q)}{\sigma^2(1)} \qquad (1)$$

where $\sigma^2(q)$ is 1/q the variance of the q-differences and $\sigma^2(1)$ is the variance of the first differences.

$$\sigma^2(q) = \frac{1}{m}\sum_{i=q}^{nq}\left(X_i - X_{i-q} - q\hat{\mu}\right)^2 \qquad (2)$$

where

$$m = q(nq - q + 1)\left(1 - \frac{q}{nq}\right)$$

and

$$\sigma^2(1) = \frac{1}{(nq-1)} \sum_{i=1}^{nq} \left(X_t - X_{i-1} - \hat{\mu}\right)^2 \qquad (3)$$

where

$$\hat{\mu} = \frac{1}{nq}\left(X_{nq} - X_0\right)$$

They develop test statistics both for homoscedastic and hetroscedastic increments. Since it is the hetroscedasticity in the data that is of interest, we use the more robust hetroscedastic test statistic that uses overlapping intervals. The test statistic is :

$$z^*(q) = \frac{VR(q)-1}{\left[\phi^*(q)\right]^{1/2}} \sim N(0,1) \qquad (4)$$

where

$$\phi^*(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q}\right]^2 \hat{\delta}(j)$$

and

$$\hat{\delta}(j) = \frac{\sum_{i=j+1}^{nq} \left(X_i - X_{i-1} - \hat{\mu}\right)^2 \left(X_{i-j} - X_{i-j-1} - \hat{\mu}\right)^2}{\sum_{i=1}^{nq} \left[\left(X_i - X_{i-1} - \hat{\mu}\right)^2\right]^2}$$

b. Non Parametric Runs Test.

Yet another issue of interest in security markets is the informational efficiency or predictability of prices based on a given information set. Empirical work in this area has proceeded along a number of different lines including the use of different information sets as predictors, examination of short-term versus long-term horizons, and the documentation of seasonal patterns that are inconsistent with established asset pricing models. The cumulative evidence on whether markets are efficient is rather mixed. By and large however, weak form efficiency has stood up as a reasonable working hypothesis.

The runs test determines whether successive price changes are independent. Unlike its parametric equivalent serial correlation test of independence, the runs test does not require returns to be normally distributed. A run is a sequence of successive price changes with the same sign. If the return series exhibit greater tendency of change in one direction, the average run will be longer and the number of runs less than that generated by a random process. To assign equal weight to each change and to consider only the direction of consecutive changes, each change in return was classified as positive (+), negative (-), or no change (0). The runs test can also be designed to count the direction of change from any base, for instance a positive change could be one where the return is greater than the sample mean, a negative change where the return is less than the mean and zero change representing a change equal to the mean. The actual runs (R) are then counted and compared to the expected number of runs (m) under the assumption of independence as given in (5) below,

$$m = \frac{\left[N(N+1) - \sum_{i=1}^{3} n_i^2 \right]}{N} \tag{5}$$

where N is the total number of return observations, n_i is a count of price change in each category. For a large number of observations (N>30), m approximately corresponds to a normal distribution with a standard error (σ_m) of runs as specified in (6).

$$\sigma_m = \left[\sum_{i=1}^{3} n_i^2 \left\{ \sum_{i=1}^{3} n_i^2 + N(N+1) \right\} - 2N \sum_{i=1}^{3} n_i^3 - N^3 \right]^{\frac{1}{2}} \tag{6}$$

The standard normal Z-statistic (Z = (R − m)/ σ_m) can be used to test whether the actual number of runs are consistent with the independence hypothesis. When actual number of runs exceed (fall below) the expected runs a positive (negative) Z value is obtained. Positive (negative) Z value indicates negative (positive) serial correlation in the return series.

c. Estimating the True Index-Correcting for Infrequent Trading.

To separate the effects of infrequent trading, we apply a correction to the observed index by using a methodology that employs the Beveridge and Nelson (1981) decomposition of the index into its permanent and cyclical component. If we denote by $\widetilde{X}_t^o$ the log of the true unobservable index corresponding to X_t^o the log of the observed index, it can be shown that the permanent component of the log of the observed index equals the log of the true unobserved index. See Jokivuolle (1996) for a proof of this proposition. The notation follows Jokivuolle (1996). Specifically, the permanent component of the Beveridge and Nelson decomposition of an infinite order MA process[2] can be written as,

$$\widetilde{X}_t^o = X_t^o + \lim_{T \to \infty} \left[\sum_{j=1}^{T-t} \hat{R}_t^o(j) - (T-t)\mu \right],$$

where $\hat{R}_t^o(j)$ is the optimal forecast of $\hat{R}_{t+j}^o$ made at time t, and μ is the slope of the ARMA process. Again following the notation in Jokivuolle (1996), letting $y_t^o = \hat{R}_t^o - \mu$, the permanent component can be written as,

$$\widetilde{X}_t^o = X_t^o + \lim_{T \to \infty} \left[\sum_{j=1}^{T-t} \hat{y}_t^o(j) \right] \tag{7}$$

[2] It is well known that any ARMA(p,q) process can be represented as an infinite order MA process.

The decomposition can be implemented by using an algorithm provided by Newbold (1990) to evaluate the second term on the right hand side.

$$\underset{T\to\infty}{Lim}\left[\sum_{j=1}^{T-t}\ \hat{y}_t^o(j)\right]=\sum_{j=1}^{q}\hat{y}_t^o(j)+(1-\phi_1.....-\phi_{p1})^{-1}\sum_{j=1}^{p}\sum_{i=j}^{p}\phi_1\hat{y}_t^o(q-j+1) \qquad (8)$$

$$\hat{y}_t^o(i)=y_{t+1}^o\ \forall i\leq 0$$

where p and q represent the order of the ARMA(p,q) process followed by the log of the observed index.

4. Data and Results

Data

The data consist of daily index values of the 30 bell weather stocks that trade on the BSE. This index popularly known as the "Sensex" is normalized to a starting value of 100 on April 1, 1979. The 30 stocks chosen from a universe of about 7000 scrips, accounts for about 38% of the total market capitalization and is intended to represent the core important groups in the market. Appendix 1 provides a list of the stocks currently in the index and the corresponding market capitalization. The daily data covers the period May 1990 to March 1999 for a total of 1964 observations. Relevant summary statistics for market index are provided in table 1 below.

Table 1

Summary statistics of BSE market daily index returns (%)[*],
May 1990 to March 1999.

Panel A	*BSE Index returns(%)*
Mean	0.0764
Median	0.0325
Maximum	12.3415
Minimum	-13.6607
Std. Dev.	2.0038
Skewness	0.0171
Kurtosis	7.7007
Jarque-Bera	1808.329
Probability	0.0000
Observations	1964

[*]Daily returns are computed as $R_t = 100 * \ln\left(\frac{P_t}{P_{t-1}}\right)$

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For the time period considered, the BSE experienced an average daily return of 0.0764% corresponding to an annualized return of 27.9%. Significant deviations from normality of the continuous return can be seen from the reported Jarque-Bera test statistic.

Results

In this section we provide the results of our empirical analysis of the BSE equity market. The results are presented in three parts. In the first part, details are provided for the index corrected for infrequent trading using the Beveridge and Nelson (1981) methodology described in the previous section. In part two, the variance ratio test for the random walk hypothesis is carried out and comparisons made between the observed and the corrected true index. Part three provides the results of the non parametric runs test to assess weak form efficiency of independence in price changes.

a. Estimating the True Index.

The first step in the decomposition procedure lies in identifying the underlying process for the observed log relatives. Sample autocorrelations and partial autocorrelations of the log relatives were examined. The log relatives of the index exhibits a single significant spike in its autocorrelation at lag one, with no additional lags that are economically meaningful, supporting the choice of a MA(1) process. Thus the observed index returns can be represented as $R_t^o = \mu + \theta\varepsilon_{t-1}^o + \varepsilon_t^o$, where R_t^o represents the log relative in the *observed* index level and μ the slope of the ARMA process.

Estimated ARMA coefficients are reported in Panel A of table 2 and can be seen to be highly significant.

Table 2

Estimated ARMA coefficients for BSE Index returns and descriptive statistics of the observed vs the corrected returns, May 1990 to March 1999.

The BSE index is modeled as : $R_t^o = \mu + \theta\varepsilon_{t-1}^o + \varepsilon_t^o$, where R_t^o is the log relative of the observed index levels. The log of the corrected index level is estimated as: $X_t^o + \theta\varepsilon_t$, where X_t^o is the log of the observed index level.

Panel A:	***Coefficient (Standard Error)***
μ	θ
0.0764(0.0507)	0.1285(0.0224)

(Number in parenthesis are standard errors)

Panel B: Descriptive Statistics, Observed vs Corrected Returns(%)

	Observed	Corrected
Mean	0.0764	0.0771
S.D.	2.0038	2.2447
ρ1(a1)[1]	0.117(0.117)	-0.005(-0.005)
ρ2(a2)	-0.031(-0.045)	-0.035(-0.035)
ρ3(a3)	0.038(0.048)	0.039(0.039)
ρ4(a4)	0.028(0.016)	0.026(0.025)
ρ5(a5)	-0.020(-0.023)	-0.022(-0.019)
Correlation	0.9667	

***Significant at the 1% level.

[1] ρ_i is the autocorrelation at lag i, and a_i is the partial autocorrelation coefficient. Correlation measures the correlation between the observed and the corrected index returns The corrected indices using (8) from the previous section are generated as $X_t^o + \theta\varepsilon_t^o$.

A summary of descriptive statistics for the observed and the corrected indices is shown in panel B of table 2. We highlight two aspects of the corrected index. One, note the high degree of correlation between the observed and corrected index, this is a necessary condition of the correcting methodology and validates the efficacy of the procedure. Second, note that the variability of the corrected series is higher than that of the observed index. Intuitively, the correction methodology is implicitly removing the smoothing that is symptomatic of a series that is subject to infrequent trading and updating of prices.

Appendix 2 plots the Acf and the Pacf of both the observed and corrected series. It can be seen that the spike at lag one disappears when the index is corrected.

b. Variance Ratio Test

The RWH for each of the markets is tested using the variance ratio test described in section 3. The variance ratio is computed for multiples of 2, 4, 8, and 16 periods, with the one-period return used as the base. Results for the observed and the corrected indices are shown in panel A and B of table 3 respectively.

Table 3

Variance ratio estimates and hetroscedastic test statistics for the BSE Stock Index, May 1990 to March 1999.

The variance ratios are defined as the ratio of the $(1/q)\sigma^2_q$ to σ^2_1 for values of q = 2, 4, 8, and 16, where σ^2_i is the variance of the index return defined as $100*\ln(P_t/P_{t-i})$. The hetroscedastic consistent test statistic is reported in parentheses. Panel B shows the results for the index, corrected for infrequent trading.

Panel A: Log relatives of the observed index levels				
	Number of Periods			
	2	**4**	**8**	**16**
BSE Index	1.1173***	1.1629***	1.2103***	1.3359***
Test Statistic	(0.0132)	(0.0243)	(0.0382)	(0.0555)
Probability	0.0000	0.0000	0.0000	0.0000
Panel B: Log relatives of the corrected index levels				
	Number of Periods			
	2	**4**	**8**	**16**
BSE Index	0.9954	0.9765	0.9907	1.0776
Test Statistic	(0.0131)	(0.0244)	(0.0386)	(0.0561)
Probability	0.7244	0.3358	0.8104	0.1668

*** Indicates rejection of the RWH at the 0.01 level.

When the observed indices are used , the RWH is strongly rejected ; the variance ratio increasing with the aggregation interval. In contrast, when the corrected index is used, the RWH cannot be rejected.

c. Runs test for weak form efficiency.

In this section we report results of weak from efficiency using the non parametric runs test. Since the return data for the BSE market does not conform to the normal distribution (Jarque-Bera test statistic is reported in Table 1), the runs test was considered more appropriate than a parametric serial correlation test. The skewness and kurtosis statistic indicate positive skewness of returns which are significantly more peaked than a standard normal distribution. To test the weak-form efficiency, we examine in this section the independence of price changes using the runs test. Results of the runs test are shown in Table 4, both for the observed index and for the index corrected for infrequent trading.

Table 4

Results of runs test for the BSE Stock Index, May 1990 to March 1999, observed vs corrected index levels.

The *runs test*, tests for a statistically significant difference between the expected number of runs vs. the actual number of runs. A run is defined as a sequence of successive price changes with the same sign. n(+)/n(-)/n(0) represent the number of positive/negative/zero price changes. Panel B shows the results for the index, corrected for infrequent trading.

Panel A: Observed index levels.	
	BSE
Observations (N)	1964
n(+)	1001
n(-)	957
n(0)	6
Expected runs (m)	988
Actual runs (R)	854
Standard Error (σ_m)	22.07
Z-statistic	-6.092***

Panel B: Corrected index levels.	
	BSE
Observations (N)	1963
n(+)	990
n(-)	973
n(0)	0
Expected runs (m)	982
Actual runs (R)	932
Standard Error (σ_m)	22.15
Z-statistic	-2.277

***Indicates rejection of the null that successive price changes are independent at the 1% level

In Panel A for the observed index, the actual number of runs (R) can be seen to fall short of the expected number of runs under the null hypothesis of stock return independence. The resulting negative z value indicates positive serial correlation. The runs test results show that the successive returns are not independent at the 1% level (critical value of -2.33). When the index is corrected for infrequent trading, the results are reversed, the expected and actual number of runs are significantly close. Based on the corrected index we cannot reject weak form efficiency; correcting for non-synchronous prices in this case leads to a reversal in the inference on market efficiency.

The results in this section make an important point, in that, infrequent trading and non-synchronous prices can significantly affect the conclusions drawn from efficiency and random walk tests. Explicitly correcting equity indices for infrequent trading, as done here, can therefore produce more robust tests of efficiency.

5. Conclusions

It has been known for some time that infrequent trading make inferences drawn from efficiency tests imprecise, particularly so for thinly traded emerging markets. Researchers however have continued to use the observed index levels in their analysis, and not surprisingly the extant literature on emerging markets has predominantly rejected the efficient markets hypothesis.

To mitigate the confounding effect of non-synchronous prices on efficiency and random walk tests, the true underlying index for the Bombay Equity Markets is estimated, by applying the Beveridge and Nelson (1981) decomposition to the observed index level. The RWH and market efficiency hypotheses are assessed using the variance ratio test and the non parametric runs test. Consistent with results in the literature for similar emerging markets, the RWH and weak form efficiency is rejected when the observed index is used. In contrast, inferences are reversed. with the use of the corrected true index. The corrected index shows that successive price changes are independent , implying weak form efficiency. Results presented in this paper have practical implications when assessing the efficiency of thinly traded markets, where explicitly correcting for infrequent trading may serve to produce more robust test results.

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Appendix 1
Stocks included in the Sensex Index.

Security Name	Market Capitalization (Billions of Indian Rupees)
RIL	637.69
Hind Lever	409.21
Infosys Tech	290.97
SBI	249.47
ITC Ltd.	208.87
Ranbaxy Labs	182.89
ICICI Banking	137.02
HDFC	128.67
Hind PetrlmC	120.13
TISCO	112.27
TELCO	111.83
BHEL	104.05
Hindalco	94.17
DrReddyLab	87.35
L&T	87.07
Bajaj Auto	85.87
Satyam Computers	80.99
MTML	75.41
Hero Honda	64.71
Cipla	63.27
Grasim Inds	62.70
BSES	56.43
Nestle	56.08
Zee Telefilms	53.56
HCL Technolog	53.48
GujAmbujaCem	37.57
ACC	36.48
Glaxo India	34.94
CastrolIndia	24.96
ColgatePalmo	19.75

Source: Bombay Stock Exchange. Market values as of October 8, 2003.
Note: The composition of the index is subject to periodic review, stocks may be dropped or added to maintain the representative nature of the Sensex index. In its recent history, major changes were done on August 19, 1996 when 15 stocks were replaced, and on April 10, 2000 when 4 stocks were replaced.

Appendix 2
Plots of the ACF and PACF of the Observed and Corrected Index.

Corrected Index returns

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>| |</td><td>| |</td><td>1</td><td>-0.005</td><td>-0.005</td><td>0.0512</td><td>0.821</td></tr>
<tr><td>| |</td><td>| |</td><td>2</td><td>-0.035</td><td>-0.035</td><td>2.4086</td><td>0.300</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>0.039</td><td>0.039</td><td>5.3831</td><td>0.146</td></tr>
<tr><td>| |</td><td>| |</td><td>4</td><td>0.026</td><td>0.025</td><td>6.6752</td><td>0.154</td></tr>
<tr><td>| |</td><td>| |</td><td>5</td><td>-0.022</td><td>-0.019</td><td>7.6019</td><td>0.180</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>-0.013</td><td>-0.013</td><td>7.9558</td><td>0.241</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>-0.011</td><td>-0.015</td><td>8.1963</td><td>0.316</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>-0.019</td><td>-0.019</td><td>8.9197</td><td>0.349</td></tr>
</table>

Observed Index returns

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>|* |</td><td>|* |</td><td>1</td><td>0.117</td><td>0.117</td><td>26.908</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>2</td><td>-0.031</td><td>-0.045</td><td>28.759</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>0.038</td><td>0.048</td><td>31.570</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>4</td><td>0.028</td><td>0.016</td><td>33.107</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>5</td><td>-0.020</td><td>-0.023</td><td>33.908</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>-0.017</td><td>-0.012</td><td>34.509</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>-0.015</td><td>-0.016</td><td>34.967</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>-0.010</td><td>-0.006</td><td>35.164</td><td>0.000</td></tr>
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