E C O N O M I C S   B U L L E T I N

Long memory in a small stock market

Jussi Tolvi
University of Turku

Abstract

The presence of long memory in Finnish stock market return data is tested using nonparametric methods. The data set has daily returns on six indices and forty companies. Depending on the testing method used, statistically significant long memory is detected in 24% to 67% of the series. This is considerably more than what is usually found in data of this kind.

This paper was written as a Visiting Research Fellow at Leeds University Business School. I am also grateful to two foundations, Osuuspankkiryhmän tutkimussäätiö and Suomen arvopaperimarkkinoiden edistämissäätiö, for financial support.
Citation: Tolvi, Jussi, (2003) "Long memory in a small stock market." *Economics Bulletin,* Vol. 7, No. 3 pp. 1−13
Submitted: March 21, 2003. **Accepted:** May 19, 2003.
URL: http://www.economicsbulletin.com/2003/volume7/EB−03G10001A.pdf

1. Introduction

Long memory in time series can be defined as autocorrelation at long lags, of up to hundreds of time periods. The potential presence of such long memory in stock market returns has been a popular research topic, although the results of these studies have been mixed. There are a number of articles where very little evidence for long memory has been found (references to these can be found in Hiemstra & Jones, 1997). On the other hand, there are also several studies where at least some evidence of long memory has been detected in monthly, weekly and daily stock market returns by, for example, Crato (1994), Cheung and Lai (1995), Barkoulas and Baum (1996), Barkoulas, Baum, and Travlos (2000), Sadique and Silvapulle (2001), Henry (2002) and Tolvi (2003). The results in these articles, however, are often quite conflicting across different tests, and also not robust to minor changes in the testing methods.

Most of the earlier work focuses only on stock market indices, although for example Barkoulas and Baum (1996) and Hiemstra and Jones (1997) examine also individual U.S. stocks.[1] Both of these find evidence of statistically significant long memory only for a few stocks. On the other hand, Panas (2001) examines the daily returns of 13 Greek stocks, and finds statistically significant long memory in most of the series.

Since small markets do not always seem to behave as expected, and more precisely, the efficient market hypothesis may not necessarily hold for returns of stocks in small markets, it is more likely that long memory will be detected in them. This point was raised by Barkoulas et al. (2000), who examined weekly returns in the Greek stock market during the 1980s, and found clear evidence of significant long memory (see also Sadique & Silvapulle, 2001). Similarly, Wright (2001) examines a number of emerging markets and finds that long memory is more often found in them than in developed markets.

The data used in this article has daily stock market returns for a number of Finnish companies and stock market indices. Since the Finnish stock market is rather small, the hypothesis of this article is that more evidence for long memory will be found in the data, than what is usually found in the markets of developed countries. To examine this hypothesis, several types of tests will be used, to avoid certain problems from influencing the results. These will be discussed in detail in the next section.

An interesting further topic to examine is the question of which series, if any, have statistically significant long memory. In other words, what are the characteristics of an individual stock that are related to the presence of long memory. Hiemstra and Jones (1997) report that U.S. stocks with heavy-tailed return distributions and high (risk-adjusted) average returns are more likely to have long memory. This question will also be considered using the Finnish data set.

[1] Based on theoretical work, one might expect to find long memory particularly in indices. One reason for this is the fact that long memory can be created by aggregating certain types of short memory series (see, e.g., Granger, 1980).

2. Methods

The long memory model used in this article is the autoregressive fractional integration moving average, or ARFIMA(p, d, q), model. For the observed series $y_t, t = 1, \ldots, T$, it is given by

$$\phi(L)(1 - L)^d (y_t - \mu) = \theta(L)\varepsilon_t, \tag{1}$$

where L is the lag operator $(L^j y_t = y_{t-j})$, $\phi(L) = 1 - \phi_1 L - \ldots - \phi_p L^p$ is the autoregressive polynomial, and $\theta(L) = 1 + \theta_1 L + \ldots + \theta_q L^q$ the moving average polynomial. The differencing parameter d need not be an integer, but integer values of d lead to traditional ARIMA models. The fractional differencing operator $(1 - L)^d$ is defined for non-integer d by an infinite binomial expansion

$$(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-L)^j. \tag{2}$$

In addition, the usual assumptions that $\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$, that all roots of the AR and MA polynomials are outside the unit circle, and that they do not have common roots, will be made.

The long range properties of such series depend on the value of d. For $d \in (0, 0.5)$ the (theoretical) autocorrelations are all positive. They decay hyperbolically to zero as the lag length increases, compared to the usual exponential decay in the case of a stationary ARMA model with $d = 0$. For $d \in (-0.5, 0)$ the series is said to exhibit intermediate memory. In this case the autocorrelations are all negative. For $d \geq 0.5$ the series are no longer covariance stationary, and have infinite variance. For a more detailed discussion see, for example, Baillie (1996).

There exist a large number of methods to test for long memory. In this article two types of tests will be used. The nonparametric estimator of Geweke and Porter-Hudak (1983), based on frequency domain methods, has perhaps been most often used in financial research. First, let $I(\xi)$ be the periodogram of the demeaned series $y_t - \bar{y}$ at frequency ξ, that is

$$I(\xi) = \frac{1}{2\pi T} \left(\sum_{t=1}^{T} (y_t - \bar{y}) e^{-it\xi} \right)^2. \tag{3}$$

The spectral regression of the GPH estimator is then computed by regressing a number of the logarithmic periodograms on a constant and a nonlinear function of the frequencies, according to

$$\ln\{I(\xi_j)\} = \beta_0 + \beta_1 \ln \left[\sin^2 \left(\frac{\xi_j}{2} \right) \right] + \eta_j, \tag{4}$$

where $j = 1, \ldots, \nu$ $(\nu \ll T)$ is the number of periodogram ordinates used in the regression, $\xi_j = (2\pi j)/T$ and η_j is an error term. The GPH estimate of d is the negative of the OLS estimate of β_1 in this regression. The presence of statistically significant long memory can then be tested by a simple t test of the estimate of d, the null hypothesis of no long memory corresponding with a parameter value of zero.

Although this estimator is relatively easy to compute, it has some potential problems, which should be somehow taken into account. First, to use this method, a choice of ν must first be made. Usually it is some simple function of the sample size T. Perhaps the most common choice, traditionally used in this kind of research, is to set $\nu = T^{0.5}$. This choice may not, however, be the best possible choice in every situation, and may lead to biased results. There exist some theoretical work on this topic, but no easily applicable rule for the choice of ν.

Nevertheless, one possibility for an empirical, data driven choice of ν is to compute the estimate of d with different values of ν, plot them, and search for a flat region in the plot. In such a region both the variance and the bias of the estimate should be small, as suggested by Taqqu and Teverovsky (1996). To find appropriate values for the data set used in this article, GPH estimates were computed for a large number of series, using values of ν ranging from 10 to $T/2$ (which is the maximum usable value). Values around $\nu = T^{0.5}$ lead to very random results, and $\nu = T^{0.8}$ is therefore perhaps a better choice, and will be used in what follows.

In the presence of short range dependencies, such as autoregressive or moving average terms in the data generating process, the GPH estimator is known to be biased in small samples (Agiakloglou, Newbold, & Wohar, 1992). This may not be a serious problem in financial data, but some care must probably be taken, and any short term dependencies removed from the data. In this article this is done by first estimating either an AR(1) or an MA(1) model (the better fitting model is selected) for the series, and computing the long memory tests both on the original series and on the residuals obtained from the AR or MA model.

The GPH estimator seems to be robust against minor nonnormality of the observations and ARCH effects, which are well known properties of financial data (Andersson & Gredenhoff, 1998). On the other hand, large isolated outliers in the data can bias the estimate of the long memory parameter d towards zero (see Tolvi, 2001, for some results). Any potential outliers are therefore in the empirical part of this article first removed from the data, as in Granger and Ding (1995). They simply winsorize the returns such that any return larger than three standard deviations (of the particular return series) is set to equal three standard deviations, and any return smaller than minus three standard deviations is set to equal minus three standard deviations.

Similarly, trends, level shifts and other structural breaks in the data can also affect the estimates. To inspect whether such trends are influential, the long memory parameter can also be estimated using a more robust estimator as well as the traditional GPH estimator. The robust estimator is called tapered GPH, which is based on a weighted version of the periodogram (see Hurvich & Ray, 1995). Velasco (1999) and Sibbertsen (2003) show that this estimator is less biased by at least certain kinds of trends in the data than the traditional GPH estimator.

In addition to the GPH estimates and hypothesis tests based on them, another testing procedure is also used in this article. Robinson (1994) has proposed a Lagrange Multiplier (LM) test to test whether any hypothetical fractional integration parameter value d_0 is supported by the data. To compute the test, the series is first differenced using the hypothetical fractional integration value, and the obtained series $\hat{u}_t = (1-L)^{d_0} y_t$ is used in the test. The test statistic is

$$\hat{r} = \frac{T^{1/2}}{\hat{\sigma}_u^2} \frac{\hat{a}}{\hat{A}^{1/2}}, \tag{5}$$

where $\hat{\sigma}_u^2$ is the variance of the $\hat{u}_t$ series,

$$\hat{A} = \frac{2}{T} \sum_{j=1}^{T-1} \left(\log |2 \sin \frac{\xi_j}{2}| \right)^2, \tag{6}$$

$$\hat{a} = \frac{-2\pi}{T} \sum_{j=1}^{T-1} \log |2 \sin \frac{\xi_j}{2}| I(\xi_j), \tag{7}$$

$\xi_j = 2\pi j/T$, and $I(\xi_j)$ is the periodogram of the $\hat{u}_t$ series. Under the null hypothesis of $d = d_0$, and assuming that the true u_t is a white noise series, $\hat{r}$ has a standard normal distribution. By computing the test for a range of values of d, and finding the values for which the null hypothesis can not be rejected gives an indication of possible long memory in a series. If the test does not reject a certain value of d_0, it can be taken as support that the series is integrated of (fractional) order d_0. These LM tests are in this article computed for a number of values of d_0, and 95% confidence intervals computed for the supported values of fractional integration as in Gil-Alana (2002).

3. The data

The data, which are daily observations, come from the EcoWin database. Table I lists all the series with some information on them and descriptive statistics. The returns are computed as logarithmic differences of the original price and index series. First, six indices are included in the data set. The three general indices are the HEX General, which is a value-weighted index of all stocks traded in the Helsinki stock exchange, HEX 20, which is based on the 20 most traded stocks, and HEX Portfolio, which has a limit on the maximum weight one company can have (since the other indices are dominated by only a few of the largest companies, especially Nokia). The three industries, for which an index is included in the data set, are banks, the forest industry and the metal industry.

The main part of the data set consists of returns of 40 individual stocks. In selecting both the indices and the stocks to include, the main criterion was the length of the available series. I decided to discard any series with less than 1700 observations. Therefore the shortest series has 1712 observations. The longest series, the HEX 20 index, has 3761 observations starting at the beginning of January 1987. The last date of all series is the fourth of June, 2001.

Table I gives also the market values of the companies.[2] This is the market capitalization value of each stock, in millions of Euros, at the end of the sample period. The companies vary considerably in their market values, from Nokia, which was at the end of this sample among the most valuable companies in the world, to relatively small companies. The liquidity of the stocks also varies considerably. The smallest companies were not traded on all days in the sample.

Most of the series means are positive (the mean of the mean returns is 0.028), although there are also ten stocks with negative mean returns. The skewness coefficient is negative for most series, and the kurtosis coefficients are all clearly larger than three (the value for a normal distribution). Any formal normality test results will not be reported, since they are so clearly statistically significant.

4. Results

Results are only reported here on the winsorized returns with no ARMA filtering, since the filtering did not really change the results.[3] The results from the traditional GPH estimation can be found in the first three columns of Table II.

Approximately 35% of the series (16 out of 46) have statistically significant long memory at the 10% level, and 24% (11 out of 46) at the 5% level. This is considerably more than should be expected due to random variation alone, and can be taken as strong indication of the presence of long memory in these series. Three of the six indices in the data seem to have long memory with positive values of d, varying from 0.059 to 0.077. Conversely, all of the statistically significant estimates for individual companies are negative, mostly between -0.1 and -0.05 in value.

The results of the trend-robust tapered GPH estimation are not tabulated (but they are available from the author). Suffice it to note that overall, these do not differ much from those discussed above, and the number of statistically significant estimates is 18 at the 10% level and 11 at the 5% level. If the traditional estimates were noticeably more often statistically significant, one would have to consider the possibility that this is due to the presence of neglected trends. Since this does not seem to be the case, however, more trust can be placed in the obtained results.

[2] Several companies in the sample have two series of stocks. For some companies, the value of one of the series is small compared to the other one. In a number of companies (i.e. Ilkka, Kesko, Orion, Pohjola, Stockmann, Stora Enso, Wärtsilä and Ålandsbanken) this is not the case. In what follows, I have decided in all cases to use information only on the more valuable and/or more liquid of the two series.

[3] All computations for this article were made using Ox 2.20 (Doornik, 1998).

Next, the LM test (at the 5% level) was computed for several hypothetical (fractional) differencing values. The values used for the returns were -0.25 to 0.25, with increments of 0.01. The end points of the values of the differencing parameter d_0 that can not be rejected in the test are listed in the last column of Table II, giving an approximate 95% confidence interval for the fractional integration parameter.

Based on the LM test results, zero is included in the confidence interval, and the null hypothesis of $d_0 = 0$ (and therefore no fractional integration, and no long memory) can not be rejected for 33% of the series (15 out of 46). For the remaining 67% of the series (31 out of 46), zero is not in the confidence interval, and the null hypothesis of $d_0 = 0$ can be rejected at the 5% level. For these series there is therefore evidence of long memory. Note that all indices are included in this group of series. In agreement with the results from GPH estimation, the confidence intervals for the indices lie above zero, and those (statistically significant) for the individual companies lie below zero. The only exception is Raisio, for which the LM interval is $[0.02, 0.09]$.

The results from the GPH and LM tests differ therefore for several series. For example, in the case of Benefon, the GPH estimate is -0.095, which is clearly statistically significant, whereas the confidence interval based on the LM test is $[-0.05, 0.04]$. At the other extreme, for Olvi the GPH estimate is a non-significant -0.016, whereas the confidence interval is $[-0.14, -0.09]$. At the 5% level, the two tests agree on the presence of long memory for nearly half of the series (22 out of 46). For the same number (22) of series the LM test is significant, whereas the GPH test is not, and for two series the opposite is true.

The discrepancy between the results of the two testing methods is therefore quite clear. Partly it must be due to the apparently greater power of the LM test in detecting minor long memory, since according to some simple simulation experiments (not reported here in detail, but available from the author) the power of the LM test can be as high as twice that based on the GPH estimate. This point has apparently not yet been studied in detail, which would obviously be worthwhile. The effects of other potential factors, such as the two methods' robustness against various departures from their assumptions, can not be as easily determined.

As noted in the introduction, Hiemstra and Jones (1997) found that U.S. stocks with heavy-tailed return distributions and high average returns are more likely to have long memory. To find out whether similar features can be seen in this data set, logit and probit models were estimated for the results on individual companies. The dependent variable in these models has a value of one if statistically significant long memory (at the 5% level in the traditional GPH estimation or in the LM test) was detected for the stock, and zero otherwise. Independent variables included in the models were the mean, standard deviation and kurtosis of the returns, and the market capitalization value of each company.[4]

First, a dummy was created based on whether the GPH estimate is statistically significant or not. In the estimated logit and probit models for this variable, the return mean and kurtosis coefficients are significant at the 10% level, the other variables are not. Here, kurtosis has a positive coefficient, which agrees with the results of Hiemstra and Jones, whereas the mean return has a negative coefficient, in contrast to the positive one found by Hiemstra and Jones. Next, a dummy was created based on the significance of the LM test. In models using this variable, the market value and standard deviation variables have statistically significant coefficients at the 5% level, and the kurtosis variable at the 10% level (in a probit model, but not quite in a logit model). Kurtosis has a positive coefficient, whereas the other two have a negative coefficient. The results with respect to kurtosis are therefore again in line with Hiemstra and Jones, whereas with other variables this is not the case. The negative coefficient of the market value is at least what one would expect, since smaller companies, the stocks of which are also less actively traded, should be the ones most likely to have temporal dependence (including long memory) in their returns.

5. Conclusions

The presence of long memory in Finnish stock market returns was examined in this article. Two testing methods were used, and however the results are interpreted, there would appear to be a considerable number of series with statistically significant long memory. Clear evidence for long memory was found in the returns of all six indices, and in nearly two thirds of the 40 individual stocks by the LM testing method. Fewer series were found to have long memory in the GPH estimation results, but this may be due to the lower power of the method, compared to the LM test.

It seems therefore, that the hypothesis of more frequent presence of long memory in small markets is supported by the results. More evidence for return long memory can be found in this data set, than what has earlier been found in, for example, the U.S. stock markets. Some evidence was also found for the hypothesis that the presence of long memory in the returns of individual stocks is correlated with the sample moments. In this data set kurtosis is positively correlated with the presence of long memory, whereas mean and standard deviation seem to be negatively correlated.

[4] Since the market value of Nokia is so obviously greater than that of any other company in the sample, the analysis was repeated without that company. The results, however, are the same in both cases.

References

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

Andersson, M. K. and M. P. Gredenhoff (1998) *"Robust testing for fractional integration using the bootstrap"* Working Paper Series in Economics and Finance No. 218, Stockholm School of Economics.

Baillie, R. T. (1996) "Long memory processes and fractional integration in econometrics" *Journal of Econometrics* **73**, 5–59.

Barkoulas, J. T. and C. F. Baum (1996) "Long term dependence in stock returns" *Economics Letters* **53**, 253–259.

Barkoulas, J. T., C. F. Baum and N. Travlos (2000) "Long memory in the Greek stock market" *Applied Financial Economics* **10**, 177–184.

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

Crato, N. (1994) "Some international evidence regarding the stochastic behavior of stock returns" *Applied Financial Economics* **4**, 33–39.

Doornik, J. A. (1998) *Object-oriented matrix programming using Ox 2.0.*, Timberlake Consultants: London.

Geweke, J. and S. Porter-Hudak (1983) "The estimation and application of long memory time series models" *Journal of Time Series Analysis* **4**, 221–238.

Gil-Alana, L. A. (2002) "Confidence intervals for fractionally integrated hypotheses in the real output across Europe" *Applied Economics Letters* **9**, 407–409.

Granger, C. W. J. (1980) "Long memory relationships and the aggregation of dynamic models" *Journal of Econometrics* **14**, 227–238.

Granger, C. W. J. and Z. Ding (1995) "Some properties of absolute return: An alternative measure of risk" *Annales d'Economie et de Statistique* **40**, 67–91.

Henry, O. T. (2002) "Long memory in stock returns: some international evidence" *Applied Financial Economics* **12**, 725–729.

Hiemstra, C. and J. D. Jones (1997) "Another look at long memory in common stock returns" *Journal of Empirical Finance* **4**, 373–401.

Hurvich, C. and B. Ray (1995) "Estimation of the memory parameter for nonstationary or noninvertible fractionally integrated processes" *Journal of Time Series Analysis* **16**, 17–42.

Panas, E. (2001) "Estimating fractal dimension using stable distributions and exploring long memory through ARFIMA models in Athens Stock Exchange" *Applied Financial Economics* **11**, 395–402.

Robinson, P. M. (1994) "Efficient tests of nonstationary hypotheses" *Journal of the American Statistical Association* **89**, 1420–1437.

Sadique, S. and P. Silvapulle (2001) "Long-term memory in stock market returns: international evidence" *International Journal of Finance and Economics* **6**, 59–67.

Sibbertsen, P. (2003) "Log-periodogram estimation of the memory parameter of a long-memory process under trend" *Statistics & Probability Letters* **61**, 261-268.

Taqqu, M. S. and V. Teverovsky (1996) "Semi-parametric graphical estimation of long-memory data" in *Athens conference on applied probability and time series. Volume II: Time series analysis in memory of E. J. Hannan* by P. M. Robinson and M. Rosenblatt, Eds., Springer: New York.

Tolvi, J. (2001) *Outliers in nonlinear time series econometrics*, Annales Universitatis Turkuensis, B 243. PhD dissertation, University of Turku.

Tolvi, J. (2003) "Long memory and outliers in stock market returns" *Applied Financial Economics (forthcoming).*

Velasco, C. (1999) "Non-stationary log-periodogram regression" *Journal of Econometrics* **91**, 325–371.

Wright, J. H. (2001) "Long memory in emerging market stock returns" *Emerging Markets Quarterly* **5**, 50–55.

Table I: Descriptive statistics

Series	T	Value	$\hat{\mu}$	$\hat{\sigma}$	$\hat{s}$	$\hat{k}$
HEX General	3500	—	0.059	1.664	-0.223	13.419
HEX 20	3761	—	0.063	1.853	-0.241	13.443
HEX Portfolio	2718	—	0.045	1.264	-0.189	5.882
HEX Banks	2305	—	0.069	2.452	-0.805	19.621
HEX Forest	2305	—	0.067	1.835	-0.035	6.360
HEX Metal	2305	—	0.041	1.274	0.032	5.648
Amer	3210	639	-0.000	2.292	0.044	7.648
Benefon	1762	23	-0.110	4.119	0.745	18.873
Finnair	1935	414	0.019	1.942	-0.557	13.180
Finnlines	1935	499	0.046	2.324	-0.145	8.570
Fiskars	1934	334	0.030	2.283	0.246	7.627
Hackman	1818	57	-0.019	2.470	-0.051	8.327
Hartwall	1818	1 174	0.112	2.994	0.338	9.821
Huhtamäki	2957	913	0.022	2.428	-0.197	14.133
Ilkka	1817	46	0.036	2.655	-0.569	23.919
Instrumentarium	3210	868	0.030	2.370	-0.390	18.313
Kemira	1712	808	0.003	2.094	-0.155	6.315
Kesko	1935	512	0.002	1.857	-0.489	14.918
Kone	2195	1 417	0.057	2.035	-0.446	9.497
Lemminkäinen	1839	221	0.009	2.061	-0.228	8.664
Leo Longlife	2339	179	0.016	2.034	-0.073	11.154
Lännen Tehtaat	1840	70	0.004	2.346	-0.044	9.273
Martela	1840	46	0.067	2.446	-0.052	11.700
Metso	3210	1 724	0.009	2.754	0.257	10.767
Nokia	1999	160 609	0.192	3.039	-0.153	7.768
Okobank	1935	446	0.053	2.211	0.195	12.164
Olvi	1840	37	-0.024	1.892	0.142	9.369
Orion	1930	672	0.001	1.988	-0.262	7.085
Outokumpu	1930	1 308	-0.009	2.428	0.092	8.195
Partek	2195	561	0.030	2.398	0.254	6.820
Pohjola	3091	800	0.016	3.408	-0.940	18.758
Polar	3210	47	-0.140	4.119	-1.007	25.011
Raisio	1838	199	-0.005	3.619	0.381	24.528
Rautaruukki	1935	625	-0.025	2.122	-0.002	5.655

(*Continued*)

Table I: Continued

Series	T	Value	$\hat{\mu}$	$\hat{\sigma}$	$\hat{s}$	$\hat{k}$
Silja	2194	64	-0.058	3.573	0.457	11.480
Stockmann	2067	308	0.041	2.032	-0.043	8.529
Stora Enso	2178	9 718	0.057	2.338	-0.037	6.737
Talentum	2976	145	0.068	3.724	0.759	15.920
Tamro	1935	333	-0.002	2.166	0.432	8.122
Tietoenator	1935	2 620	0.142	3.082	-0.578	10.998
Tulikivi	1840	23	0.009	2.308	0.026	10.579
Turkistuottajat	2120	20	0.071	3.239	-0.113	11.265
UPM-Kymmene	2957	9 261	0.038	2.304	-0.125	6.172
Vaisala	1840	498	0.055	2.054	0.147	7.262
Wärtsilä	2696	1 023	0.065	2.272	0.231	9.299
Ålandsbanken	3210	92	0.025	1.843	-0.748	19.748

Notes: T is the sample size, Value is the market capitalization value in millions of Euros at the end of the sample, $\hat{\mu}$, $\hat{\sigma}$, $\hat{s}$ and $\hat{k}$ are the sample mean, standard deviation, skewness and kurtosis.

Table II: Long memory test results

Series	GPH			LM
	$\hat{d}$	$SE(\hat{d})$	p	
HEX General	0.059	0.025	0.020	[0.05, 0.09]
HEX 20	0.040	0.025	0.102	[0.04, 0.08]
HEX Portfolio	0.077	0.028	0.006	[0.09, 0.14]
HEX Banks	0.000	0.030	0.994	[0.05, 0.11]
HEX Forest	-0.041	0.030	0.174	[0.07, 0.14]
HEX Metal	0.064	0.030	0.032	[0.07, 0.12]
Amer	0.019	0.026	0.474	[0.00, 0.04]
Benefon	-0.095	0.034	0.005	[-0.05, 0.04]
Finnair	0.016	0.033	0.626	[-0.07, -0.01]
Finnlines	0.016	0.033	0.629	[-0.05, 0.00]
Fiskars	-0.055	0.033	0.090	[-0.14, -0.10]
Hackman	-0.004	0.033	0.913	[-0.09, -0.03]
Hartwall	0.017	0.033	0.620	[-0.04, 0.01]
Huhtamäki	-0.071	0.027	0.008	[-0.09, -0.04]
Ilkka	-0.095	0.033	0.005	[-0.12, -0.05]
Instru	0.044	0.026	0.092	[-0.04, 0.00]
Kemira	-0.018	0.034	0.596	[-0.12, -0.06]
Kesko	-0.103	0.033	0.002	[-0.12, -0.07]
Kone	-0.057	0.030	0.064	[-0.08, -0.02]
Lemminkäinen	-0.044	0.033	0.183	[-0.11, -0.06]
Leo Longlife	-0.061	0.030	0.041	[-0.10, -0.05]
Lännen Tehtaat	-0.141	0.033	0.000	[-0.22, -0.16]
Martela	-0.041	0.033	0.212	[-0.11, -0.06]
Metso	0.010	0.026	0.700	[-0.01, 0.03]
Nokia	0.005	0.025	0.853	[-0.04, 0.00]
Okobank	-0.040	0.033	0.216	[-0.11, -0.06]
Olvi	-0.016	0.033	0.637	[-0.14, -0.09]
Orion	-0.022	0.033	0.502	[-0.11, -0.06]
Outokumpu	-0.028	0.033	0.397	[-0.06, 0.00]
Partek	-0.031	0.030	0.309	[-0.05, 0.01]
Pohjola	-0.039	0.027	0.147	[-0.06, -0.02]
Polar	-0.078	0.026	0.003	[-0.06, -0.01]
Raisio	0.010	0.033	0.755	[0.02, 0.09]
Rautaruukki	-0.059	0.033	0.072	[-0.05, 0.01]

(*Continued*)

Table II: Continued

Series	GPH			LM
	$\hat{d}$	$SE(\hat{d})$	p	
Silja	-0.022	0.031	0.462	[-0.08, -0.04]
Stockmann	-0.008	0.031	0.802	[-0.12, -0.08]
Stora Enso	-0.044	0.031	0.149	[-0.03, 0.04]
Talentum	0.005	0.027	0.865	[-0.04, 0.00]
Tamro	0.004	0.033	0.911	[-0.06, -0.01]
TietoEnator	-0.059	0.033	0.071	[-0.01, 0.07]
Tulikivi	-0.040	0.033	0.224	[-0.08, -0.04]
Turkistuottajat	-0.005	0.031	0.872	[-0.06, -0.02]
UPM-Kymmene	-0.055	0.027	0.041	[-0.05, 0.00]
Vaisala	-0.001	0.033	0.977	[-0.06, -0.01]
Wärtsilä	-0.003	0.028	0.901	[-0.01, 0.04]
Ålandsbanken	-0.022	0.026	0.398	[-0.09, -0.05]

Notes: The LM test non-rejection values are those for which the null hypothesis of fractional integration at that degree can not be rejected at the 5% level by the Robinson (1994) test.