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The Great Rebound, The Great Crash, and Persistence in British Stock Prices

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ABSTRACT

In this paper, we investigate the persistence of British stock returns over the period 1962-98 using the Variance Ratio (VR) test to check for short-range dependence and the Modified Rescaled Range (MRS) test to check for long-range dependence. A central contribution of the paper is that we investigate the role of the great rebound in stock prices in January 1975 and the crash of October 1987. These shocks, which together represent less than 1% of the data fundamentally alter the time series properties of the data, with extreme skewness, excess kurtosis, and ARCH present in the unadjusted data, but absent from much of the shock-purged data. The VR and MRS tests reveal relatively little evidence of persistence in the original data. However, the VR tests exhibit systematic and significant reversals of sign as between the original and the shock-purged data. It appears that stock prices in Britain persistently stayed away from the mean, and then reverted back towards it in just two exceptionally large jumps. The results reinforce the need for researchers to take extra care in analysing British stock market data in the post-war period.

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1. Introduction

Are stock returns predictable? This is a question which has engendered a huge volume of serious academic research and popular debate. Yet, as several recent surveys would suggest, the question is far from settled; and even the interpretation of the notion of "predictability" is subject to debate. See, *inter alia*, Fama (1991), Forbes (1996), Lo and MacKinlay (1999). The most basic hypothesis about stock return predictability is the random walk hypothesis. If (the logs of) stock prices follow a random walk, then stock returns, which are just the log price increments, are serially uncorrelated and therefore unpredictable. The random walk hypothesis has been extensively tested, but researchers keep returning to it. They do so first, because it is the most basic hypothesis about stock return predictability; and second, because tests of the random walk hypothesis appear to vary considerably in power depending *inter alia* on: the exact version of the hypothesis tested; the alternative hypothesis against which it is tested; and, not least, on the frequency, span, and country of the dataset on which it is tested. See Campbell, Lo and MacKinley (1997).

Popular alternatives to the random walk include the fads and fashions models of Shiller (1984) and Summers (1986). Summers argued that a useful statistical characterization of fashions in stock valuations is that prices have a slowly decaying predictable stationary component which induces negative autocorrelation in returns. If this model is true, the estimated stock return autocorrelations in finite samples may be negligibly small for short-horizon (daily or weekly) returns, but increase substantially as the return horizon is increased. In a study of US stock returns covering 1926-85, Fama and French (1988b) did indeed find that the proportion of the returns explained by a negative autocorrelation component increased markedly as the return horizon increased, with some 25-45% of the variation of 3-5 year returns being predictable from past returns.

A variety of procedures have been developed to test for predictability over different time horizons. Two of the most popular are Lo and MacKinley's (1988) variance ratio (VR) test and Lo's (1991) modified rescaled range (MRS) test. The former is primarily a test for short-range dependence and the latter a test for long-range dependence. Informally, short-range dependence occurs in a time series when there is some relationship between realizations at different dates, but the maximum dependence between realizations at any two dates becomes negligible as the time-span between the two dates increases. Long-range dependence exists when the dependence between realizations remains non-negligible as the time-span increases. Examples of short-range dependence include most classes of ARMA model which are integer-differenced to achieve stationarity. Long-range dependence occurs in fractionally-differenced processes. See Lo (1991) and the references cited therein for further details.

When first applied to American data, the VR test typically rejected the random walk hypothesis in favour of positive autocorrelations at short horizons (under one year) and negative autocorrelation at longer horizons, both for stock market indices and individual stocks. Positive autocorrelation in this context is often referred to as "mean *a*version" and negative autocorrelation as "mean *re*version". See *inter alia* Poterba and Summers (1988) and Lo and MacKinley (1988, 1989). Subsequent research on US data suggests that, when allowance is made for various possible biases in the VR statistic, the results are far less clear. Richardson and Stock (1989) argued that the Poterba and Summers data, which cover 1926-1985, actually provide only relatively weak evidence against the random walk hypothesis. Using related techniques, Kim, Nelson and Startz (1991) found that mean reversion is a phenomenon which is confined almost entirely to the inter-war period in the US[1]. The post-war data appear to be more consistent with either the random walk model, or with positive autocorrelation (mean aversion) at both short and long horizons. Jegadeesh (1990) also found evidence of positive autocorrelation in US data, particularly in the January returns.

Evidence from non-US data is almost equally ambiguous. Frennberg and Hansson (1993) found that Swedish stock index data covering 1919-1990 exhibit essentially the same features as that of Poterba and Summers; ie: mean aversion at short horizons and mean reversion at longer horizons. MacDonald and Power (1993) report similar evidence for a sample of individual stocks in the United Kingdom. However, neither of these papers take account of the criticisms and suggested amendments to the VR test procedures which were proposed by Richardson and

Stock (1989). Accordingly it is not clear whether their results are as robust as they appear at first sight. Claessens, Dasgupta, and Glen (1993) examined the stock market indices of 20 emerging markets and found departures from the random walk at short horizons in 11 of these markets, but, like the preceeding authors, they did not take account of the Richardson-Stock criticisms[2]. Huang (1995) studied 9 Asian stock market indices, and found that only Malaysia and Korea departed significantly from the random walk. Moreover, the VR tests suggested that the returns were mostly positively autocorrelated, irrespective of the return horizon. On the other hand, Mills (1991) found that the United Kingdom *Financial Times/Actuaries* All-Share index was predictable at horizons of one year or more (and therefore did depart significantly from the random walk), but like Huang, he found that the returns were positively autocorrelated, irrespective of the horizon.

Results of the MRS test have generally been less conflicting, with most authors finding little or no evidence of long-range dependence in a variety of US and international datasets. See, *inter alia*, Lo (1991), Hiemstra and Jones (1993), and Jacobsen (1996). Mills (1993) found little evidence of long memory in daily UK stock returns.

In this paper we test the short and long range dependence of British stock market returns using the VR and MRS tests. We have several reasons for returning to these tests. First, there has still been relatively little work of this nature on British data. Second, we use a new disaggregated monthly dataset of *Financial Times/Actuaries* industry groups (described in section 2) covering the period since the inception in 1962 of The Financial Times stock indices. This enables us to compare our results with the seminal study of Fama and French (1988b) which is one of relatively few to utilize (US) industry classifications in stock market research. The third and most important contribution of this paper is that we focus on the two major post-war stock market upheavals in Britain: the great rebound of January 1975, which was unique to Britain, and the great crash of October 1987, which was part of a world-wide collapse in stock market prices. Kim, Nelson and Startz (1988) found that mean reversion in US stock returns was largely confined to the inter-war period, an era which is generally agreed to be abnormal in several respects in comparison with the rest of US stock market history, dating at least from the mid-nineteenth century. See Schwert (1990). British historical stock market data are much less complete than those of the US (Green, 1997); but, in the 38 years since the inception of the comprehensive FTA indices, the great rebound and the great crash stand out clearly as exceptional episodes. Few studies of the relationship between post-war British stock returns and general economic data can do without a dummy variable for each of these episodes. Perron (1989) was among the first to point out that shocks and outliers can fundamentally alter the character of a time series, and our interpretation of its properties. It would be surprising if the shocks of 1975 and 1987 had not fundamentally affected British stock prices. Therefore, the two main objectives of this paper are: to test for short and long-range dependence in British data; and to evaluate the sensitivity of the test results to the two great shocks of 1975 and 1987.

The paper is organized as follows. Section 2 describes the data and methodology; section 3 reports the results of tests for short-range dependence; section 4 reports on long-range dependence; section 5 contains some concluding remarks.

2. Data and Methodology

2.1 The FTA indices

The data used in this study are monthly, and cover the period following the inception of the *Financial Times/Actuaries* (FTA) share indices, from June 1962 through August 1998 (435 observations)[3]. Monthly data are used partly for comparison with many other studies; partly because the complete run of FTA industry group data is not available at a higher frequency than monthly for much of the period; and partly because higher frequency data suffer from a number of problems such as thin trading (Lo and MacKinley, 1988). To uncover long-range dependence in any meaningful sense, it is important to have a long span of data more than a large number of high-frequency observations over a short time span. See Shiller and Perron (1988).

The 11 industries chosen for this study and their mnemonics are listed in table 1. We did not use all the components of The FTA index but aimed at a relatively wide spread of standard industrial sectors, including consumer goods, capital goods, and one commodity-based industry -- oils. We excluded utilities as the vast majority of these came into existence after 1979, and financial services because of their rather special characteristics. Because we excluded financial firms, we concentrated to some extent on the FTA500 as the measure of the market index. However, we also performed tests on the All-Share index: partly to compare with Mills' (1991) results, but also to evaluate whether the inclusion of financial firms affects the outcomes of the tests.

Table 1 about here

To develop the test methodology, we need the following definitions:

P_t = Price index for any particular industry group of the FTA indices

Y_t = Dividend(t+1)/P(t) = Annual industry dividend yield

B_t = Continuously compounded one month return on 3 month bank bills

Hence:

$R_t = Ln(P_{t+1}(1+Y_t/12)) - LnP_t$ = Continuously compounded one month total return

$X_t = R_t - B_t$ = One month excess return

$G_t = LnP_{t+1} - LnP_t$ = Continuously compounded one month change in prices

$R_{Qt} = \sum_{i=0}^{Q-1} R_{t-i}$ = The return on stocks over Q months (defined similarly for G_t, X_t)

Previous researchers have displayed some uncertainty about the precise return definition which should be used in these tests. Real returns, nominal returns (R_t), excess returns (X_t), and capital gains (G_t) have all been examined in different papers. Theory would suggest that dividends should be included in the calculation, since prices are free to adjust to changes in dividend

expected to display different stochastic properties from stock prices. Accordingly, we would argue that the nominal return ($_t$) is the cleanest and most appropriate variable to study. Excess

through the impact of the Fisher effect on the short-term interest rate (B). To maintain comparability with previous studies, we conducted VR and MRS tests on three return

R_t X_t G_t [4]. It transpired that

common finding in other comparable studies. Therefore, to avoid excessive repetition, we report our empirical results for $_t$ only. Results for $_t$ and $_t$ are available on request to the

R_t

for X and G are trivially analagous.

2.2 [5]

The VR test exploits the property of an IID random walk (in log prices) that the variance of the

Q) over which the return is calculated. The test

variance of the Q Q is large, and non-overlapping observations are

define the VR statistic (*M(Q)*

$$M(Q) = s_Q^2 / s_1^2 - 1 \qquad ...1$$

with: $$s_Q^2 = \sum_{t=Q}^{T} (R_{Qt} - Qm)^2 / QT$$

and: $$R_{Qt} = \sum_{i=1}^{Q} R_{t-i+1}$$ = the continuously compounded Q-period return.

$$m = \sum_{t=1}^{T} R_{1t} / T$$

T = the total number of observations.

Under the null of IID returns, then, as T→∞ with Q fixed, *M(Q)* has an approximate limiting normal distribution; and a standardized VR statistic is given by:

$$Z_1(Q) = \sqrt{T} M(Q)[2(2Q-1)(Q-1)/3Q]^{-0.5} \overset{a}{\sim} N(0,1) \qquad ...2$$

It can be shown that the finite sample performance of this test is substantially improved by using instead of s_Q^2, the unbiased estimate of the variance (v_Q):

$$v_Q = s_Q^2 T^2 / (T-Q+1)(T-Q) \qquad ...3$$

Since stock return series typically display time-varying variances, it is possible to develop a robust (heteroscedasticity-consistent) version of the VR statistic, which is given by:

$$Z_2(Q) = \sqrt{T}M(Q)/s(Q) \overset{a}{\sim} N(0,1) \qquad \text{...4}$$

with: $$s^2(Q) = 4\sum_{j=1}^{Q-1}(1-j/Q)^2 q(j)$$

and: $$q(j) = \frac{T\sum_{t=j+1}^{T}(R_t - m)^2(R_{t-j} - m)^2}{\left(Ts_1^2\right)^2}$$

In section 3 we report values of $M(Q)$, using v_Q as the variance estimator, for Q = 3, 6, 12, 24, and 60 months, together with values of $Z_1(Q)$ and $Z_2(Q)$ for our nominal return series: R_t. As noted in section 2.1, the results for X_t and G_t are qualitatively similar.

In their seminal contributions, Lo and MacKinley (1988, 1989) worked with a sample size which was much larger than ours, particularly in relation to the maximum return horizon; and they pointed out that the normal approximation for $M(Q)$ is likely to be unsatisfactory for large Q/T because the empirical distribution becomes increasingly skewed as Q/T increases. Accordingly, we follow Lo and MacKinley (1989), and Poterba and Summers (1988), and report Monte Carlo estimates of the empirical distribution of $M(Q)$ for comparison with the results for the $Z_1(Q)$ and $Z_2(Q)$ statistics. Moreover, in deriving the limiting distribution, Lo and MacKinley (1988) assumed that Q is fixed, so that $Q/T \to 0$ as $T \to \infty$. Richardson and Stock (1989) argued one could equally well assume that $Q/T \to$ z, where z is a fixed, non-zero fraction. This produces a different (non-normal) limiting distribution which, they argue, is a closer approximation to the small sample distribution of $M(Q)$. However, Mills (1991) simulated the empirical distribution of $M(Q)$ under each of these assumptions and found relatively little difference between the two. Accordingly, we report only the fixed-Q distribution in our Monte Carlo.

2.3 The modified rescaled range (MRS) test

The rescaled range statistic was developed to study long-range dependence against the null of short-term memory. It was introduced to finance by Lo (1991) following earlier work by Hurst

(1951) in the study of river discharges. The classical rescaled range (RS) statistic is the range of partial sums of deviations of a time series from its mean rescaled by its standard deviation:

$$RS = \frac{1}{s}\left[\underset{1\le K\le T}{Max}\sum_{j=1}^{K}(R_j - m) - \underset{1\le K\le T}{Min}\sum_{j=1}^{K}(R_j - m)\right] \qquad ...5$$

with: $m = \frac{1}{T}\sum_{j=1}^{T} R_j$; and $s = \left[\sum_{j=1}^{K}(R_j - m)^2 / T\right]^{0.5}$

Lo (1991) pointed out that the most important shortcoming of the RS statistic is its sensitivity to short-range as well as long-range dependence. He therefore proposed a modification which replaces the standard deviation of the series (*s*) by a consistent estimate of the standard deviation of the partial sum, $\Sigma(R_j\text{-}m)$. The modified statistic (MRS) is given by:

$$MRS = \frac{1}{s}\left[\underset{1\le K\le T}{Max}\sum_{j=1}^{K}(R_j - m) - \underset{1\le K\le T}{Min}\sum_{j=1}^{K}(R_j - m)\right] \qquad ...6$$

with: $s^2 = \frac{1}{T}\sum_{t=1}^{T}(R_t - m)^2 + \frac{2}{T}\sum_{j=1}^{h} w_j(h)\sum_{t=j+1}^{T}(R_t - m)(R_{t-j} - m)$

and $w_j(h) = 1 - \frac{j}{h+1}; h < T$

Lo provided Monte Carlo estimates of the significance levels of this MRS statistic; and showed that it is substantially more accurate than its classical counterpart in its ability to discriminate between long and short-range dependence. The Newey-West (1987) method is used to guarantee a positive estimate for σ^2, but care has to be taken in the choice of the maximum lag length (*h*) in the calculation of the sample autocovariances, and little practical guidance is available on this choice. In this respect, we follow previous researchers and report results for a small grid of *h*. See Lo (1991) for further details. In section 4 we report values of the MRS statistic for comparison with our tests for short-range dependence.

2.4 The great rebound of 1975 and the great crash of 1987

Chart 1 shows $Ln(P_t)$ for the FTA500. Charts 2-7 show R_{Qt} for the FTA500 for Q = 1, 3, 6, 12, 24, and 60. The two great post-war shocks in 1975 and 1987 clearly dominate the 2 base series, $Ln(P_t)$ and R_{1t}. The stock market fell steadily and sometimes sharply in the 15 months through end-December 1974. In January 1975 the rebound took place: the total return on the FTA500 was 52.6% in January, and a further 23.8% in February. A substantially more prolonged rise in prices preceeded the October 1987 crash, which was also less severe in magnitude than the 1975 rebound. The total return in October was -26.1% followed by -10.0% in November. As the return horizon increases (charts 3-7), the immediate impact of the two shocks is naturally reduced, but the persistence of their effects appears to be considerable. For example, the 5-year return rises steeply from January 1975 until the effect of the rebound drops out of the calculations in 1980, when it drops precipitously; likewise the 5-year return falls steeply from October 1987, until the effect of the crash drops out of the calculations[6].

Charts 1-7 about here

To analyse the role of these great shocks, we calculated a set of shock-purged monthly returns (R_t^*)[7] from regressions of R_t (or X_t, or G_t) on a constant and four event dummies: for January and February 1975, and for October and November 1987. The shock-purged returns are defined as: $R_t^* = R_t - \hat{b}_1 D_{7501} - \hat{b}_2 D_{7502} - \hat{b}_3 D_{8710} - \hat{b}_4 D_{8711}$; where $\hat{b}_i,\ i = 1,...,4$ are the estimated coefficients on the respective dummies. We excluded the month after each shock as well as the shock month itself, as it was generally perceived at the time to be part of the "event". However, we did also calculate R_t^* (and the other returns) using just one dummy for each event: for January 1975 and October 1987 only. Rerunning all the tests with this definition of the adjusted returns made no essential difference to the results.

Table 2 about here

Summary statistics for the unadjusted and adjusted returns are shown in table 2. In this table, Dmskew is the Davidson-MacKinnon test for skewness, which is distributed as N(0,1); Dmkurt is the Davidson-MacKinnon test for excess kurtosis, also distributed as N(0,1). See Davidson and MacKinnon (1993). The ARCH test is the standard $x^2(1)$ test for a first-order ARCH process.

The impact of the two shocks is already dramatically apparent from these basic statistics. With one exception (motors' skewness), the unadjusted returns all exhibit gross positive skewness and excess kurtosis at significance levels of 99% and (mostly) well beyond, suggesting that the returns are substantially non-normal. On the other hand, fewer than half of the shock-purged returns exhibit any skewness at all, even at the 95% level. Moreover, where significant skewness is present, it is negative rather than positive skewness. The results for kurtosis are (almost) equally striking. Although only 2 out of 13 shock-purged returns do not exhibit significant excess kurtosis at the 95% level, the statistics for excess kurtosis are nevertheless substantially lower than for the unadjusted returns. This has dramatic implications for the ARCH tests. 10 out of 13 of the unadjusted returns exhibit significant ARCH at the 95% level, and mostly higher, whereas 9 of the 13 shock-purged returns show no trace at all of an ARCH effect at the 95% level. This suggests that considerable caution needs to be excercised in the estimation and interpretation of ARCH models for the London stock market, as the results may depend critically on the treatment of just a very few outlying observations.

3. VR Test Results

Table 3 gives the $M(Q)$, $Z_1(Q)$, and $Z_2(Q)$ statistics for the total return variable (R_t). We find that $M(Q)$ is mostly positive at short horizons, but generally turns negative as the horizon is extended beyond 12 months, suggesting short-term mean-aversion and long-term mean-reversion in the returns series[8]. These results may be contrasted with some of the more recent studies cited in section 1, which found greater evidence of mean-aversion, even at longer horizons. However, our results are quite comparable to those of Fama and French (1988b), who use a similar industrial dataset, albeit for the USA, but a different methodology. The heteroskedasticity-robust statistics are generally less significant than the unadjusted statistics. However, these conclusions can only be stated very weakly, as only 4 out of 130 of the $Z_i(Q)$ statistics are significant at the 95% level, and all 4 of these are for the 3-month returns. It might be argued that a lower significance level is more appropriate in this situation, although this is not a view we would necessarily share. Even so, only 10 of the $Z_i(Q)$ statistics are significant at the 90% level. The next step is to simulate the distribution of $M(Q)$; and the results of this exercise are given in table 4[9]. The skewness of $M(Q)$ in this sample shows up clearly at the longer horizons, but the substance of the results is scarcely changed. Now, 3 out of 65 of the $M(Q)$ statistics are significant at the 95% level, and 5 at the 90% level. In summary of the above, there appears to be relatively little evidence in these data of persistence in returns on the London Stock Exchange.

Tables 3 and 4 about here

We turn next to the shock-purged series (R_t^*), results of which are given in table 5. The central feature of these results is that mean-reversion at longer horizons has completely disappeared: beyond 12 months, all the VR statistics are positive. There is some increase in the number of negative VR statistics at very short horizons (3 and 6 months), but overall, the data now suggest that stock returns are mostly mean-averting. More of these statistics are significant than was the case for the unadjusted data. At the 95% level, 20 out of 130 $Z^*_i(Q)$ statistics are significant, as are 10 out of 65 $M^*(Q)$ statistics; at the 90% level, 26 $Z^*_i(Q)$ statistics and 19 $M^*(Q)$ statistics are significant. Interestingly, the FT500 and the All-Share indices are among those that show significant mean-aversion: at 12 months, 24 months, and (at the 90% level) at 60 months. Therefore, the shock-purged returns show more evidence than the unadjusted returns of significant persistence, but overall, this evidence is still not very strong.

Table 5 about here

The central feature of the shock-purged $M^*(Q)$ statistics is the general reversals of sign in comparison with the unadjusted statistics. It is therefore of interest to enquire whether this difference is significant in and of itself. Since each normalized $Z_i(Q)$ statistic is asymptotically

$N\sim(0,1)$, it is tempting to assume independence, calculate the difference: $Z^D_i(Q) = Z_i(Q)-Z^*_i(Q)$, and then assert that, asymptotically, $Z^D_i(Q)\sim N(0,2^{0.5})$. We do in fact calculate this statistic for the record. However, it is clearly not true that $Z^*_i(Q)$ and $Z_i(Q)$, (or, *a fortiori*, $M^*(Q)$ and $M(Q)$) are independent, as they are each generated from the same data, with just 4 observations deleted to obtain the shock-purged series. We therefore also adopted the more direct approach of calculating the difference $M^D_i(Q) = M_i(Q)-M^*_i(Q)$, and working out significance levels by simulating the distribution of $M^D_i(Q)$. In each of these simulations, we first drew a time series from an $N(0,1)$ distribution, and then created shock-purged series by using OLS to delete the 4 largest observations (2 positive and 2 negative). Finally, we used these two series to calculate $M_i(Q)$, $M^*_i(Q)$, and $M^D_i(Q)$. By this means we were assured that the statistics took account of the relationship between $M_i(Q)$ and $M^*_i(Q)$. It could be argued that this procedure is defective in that the 1975 and 1987 shocks were far larger than could be expected as a result of being generated from a normal distribution. However, this is actually one of the purposes of making this comparison. *Inter alia*, we wish to establish if indeed the implications for stock returns of these two great shocks are within the bounds to be expected from a normal.

Tables 6 and 7 about here

Data for $Z^D_i(Q)$ and $M^D_i(Q)$ are shown in table 6. The simulated distribution of $M^D_i(Q)$ and significance levels for $N(0,2^{0.5})$ variables are shown in table 7. Just 4 out of 130 of the $Z^D_i(Q)$ statistics are significant at the 95% level (although these are for the FT 500 and the All-share), and a further 3 at the 90% level. This is perhaps not surprising when we consider the actual absence of independence between the two underlying data series. When however, we turn to $M^D_i(Q)$, we now find that 38 of the 65 statistics are significant at the 95% level (and a further 1 at the 90% level); and this includes all the returns at horizons of 24 months and above. However, there are relatively few significant differences at return horizons of 3 and 6 months. These results confirm our informal summary of the charts in section 2.4: the two great shocks cast a very long shadow over stock returns. More provocatively, one could assert that mean reversion in the post-1962 period is almost entirely due to the 1975 and 1987 shocks. It appears that stock prices in Britain persistently stayed away from the mean, and then reverted back towards it in just two exceptionally large jumps.

4. MRS Test Results

We turn finally to the results of the MRS tests, which are shown in table 8. These results are substantially in line with other researchers. Virtually all the MRS statistics are insignificant at the 95% level,[10] irrespective of whether the data are purged of the two great shocks. Only for paper is there any evidence at all of long-range dependence; the MRS statistic being significant at the 90% level for the original data, and at the 95% level for the shock-purged data. These results provide some evidence for the hypothesis of short-range dependence against that of long-range dependence. It is also interesting to examine the variation in the MRS as the lag length (h) used in the caculation of the sample autocovariances varies. Variations in the MRS across different values of h reflect bias in the calculated statistic arising from short-range dependence in the data. However, in our data it is clear that, for each industry and market index, the MRS statistics are actually quite stable as h varies. This suggests that any short-range dependence in the data is confined to periods of under 3 months; and this is consistent with the relative absence of short-range dependence already noted in connection with the VR tests. Turning finally to the impact of the two great shocks, *a priori*, one might expect that eliminating the shocks would increase long-range dependence, and this does appear to be broadly true for all the return series. However the increase is small or negligible in all cases, thus providing further evidence of the lack of any long-range dependence in stock prices.

Table 8 about here

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5. Concluding Remarks

In this paper, we investigated the short- and long-range dependence of British stock returns using the VR and MRS tests, and applying them to 1962-98 data from the FT industry group share indices. A central contribution of the paper is that we also investigated the importance for our findings of the great shocks of 1975 and 1987. Using the MRS test, we found little or no evidence of long-range dependence, irrespective of whether the two shocks are included in the data. The MRS statistic does increase when the two shocks are omitted, but still exhibits no substantial evidence of long-range dependence. The results for short-range dependence using the VR test are more interesting. We again found little evidence of short-range dependence for the unadjusted data, but there is more evidence of dependence when the data are adjusted for the two great shocks. However, the major feature of the VR tests is the reversal of signs as between the unadjusted and the shock-purged data: the unadjusted data exhibit mean-aversion at short horizons, turning to mean reversion at long horizons; the shock-purged data exhibit mostly mean-aversion at all horizons, especially long horizons. We then tested the difference between the VR statistics, including and excluding the shocks, and found that these differences were invariably significant. Further evidence of the impact of these two shocks was found in the basic statistics for the data, with extreme skewness, excess kurtosis, and ARCH present in the unadjusted data, but skewness and ARCH mostly absent from much of the shock-purged data, and excess kurtosis much reduced.

What do we learn from these results? It seems clear that the 1975 and 1987 shocks had a fundamental impact on the time series properties of UK stock prices - so fundamental that, in key respects, they change entirely the basic properties of the data. It is worth emphasizing that it is less than 1% of the data that fundamentally alters its characteristics. This suggests to us that future research will need to pay more attention to these shocks. For many purposes, it may be more appropriate to delete them from a research study to avoid misleading results - results which are actually based on 2 "outliers" rather than the whole dataset. *Prima facie*, the two shocks were very different in nature, and probably emanated from different causes. The 1987 crash was part of a general world-wide crash in stock values, and it followed after a long bull market. The 1975 rebound, on the other hand, was confined entirely to the UK and came after a relatively short but sharp decline in the market. Nevertheless, these two events are clearly of central importance in fully understanding the evolution of the British stock market over the last 40 years, and a more direct effort at understanding why they occurred should surely form an essential part of any future research agenda.

Footnotes

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1. This result could be related to that of Fama and French (1988a) who found evidence of a significant change in firms' dividend policy as between the inter-war and post-war years, a change which may be reflected in corresponding changes in stock price behaviour.

2. As we discuss in section 2, Lo and MacKinlay pointed out that the distribution of the VR statistic tends to be skewed, even in the relatively large samples which are typical of stock market datasets, although it does have a standard limiting distribution. Richardson and Stock emphasized the need to simulate the empirical distribution which corresponds to the sample size actually used by the investigator. This was not done by Frennberg and Hansson, or by MacDonald and Power, or by Claessens, Dasgupta, and Glen.

3. Stock market data from 1976 were extracted from DATASTREAM. Data prior to 1976, and some corrections to the DATASTREAM data were provided by The Institute of Actuaries. Data for bills were taken from Green Maggioni and Bowen (1992). Mills (1991) argued that pre-1965 data are tainted by the existence at the time of dividend controls. This is not a view we share. Actually, dividend controls were in existence in the UK for most of the 1960s and through the early part of the 1970s. Moreover, even if a firm is constrained in the dividends it can pay, theory would suggest that its stock price would adjust to make the total return equal to that required by investors in a competitive market.

4. Of course, it is more difficult to incorporate dividends or retail prices in datasets of higher frequency than monthly.

5. The exposition in this section follows Lo and Mackinley (1988, 1989).

6. Plots of the all-share index and of the industrial groups in this study produce broadly similar pictures, in the relevant respects.

7. The notation for the shock-purged VR and MRS statistics is analagous; ie. $M^*(Q)$, $Z^*_1(Q)$, $Z^*_2(Q)$, and MRS^*.

8. Qualitatively similar results were found for X_t, and G_t.

9. Simulations of $M^*(Q)$ were based on drawings from an N(0,1) distribution, with 435 observations and 10,000 replications.

10. This is a two-tailed test.

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Table 1. Financial Times/Actuaries (FTA) Share Indices: Industry Groups

Indices	
alls	All Share Index
i500	500 Industrial Shares
Capital Goods	
buil	Building Materials
elec	Electricals
enge	Engineering: General
motr	Motors and Distributors
Consumer Goods	
bwds	Breweries and Distilleries
fdmf	Food Manufacturing
leis	Entertainment and Catering
papa	Paper and Packaging
stor	Stores
text	Textiles
Other	
oils	Oil and Gas

Table 2. FTA Share Indices: Basic Statistics

	mean	std dev	skewness	kurtosis	DMskew	DMkurt	arch
	Returns including 1975 and 1987 shocks (R_t)						
buil	0.0124	0.0785	1.1369	10.5572	9.6800**	44.9458**	3.7535
elec	0.0134	0.0703	0.9077	8.0376	7.7285**	34.2189**	5.5792*
enge	0.0112	0.0677	0.3593	6.2356	3.0591**	26.5473**	18.7522**
motr	0.0122	0.0769	0.0560	1.9534	0.4767	8.3164**	11.3353**
bwds	0.0135	0.0655	0.9093	9.0383	7.7426**	38.4793**	1.7047
fdmf	0.0128	0.0617	1.4696	15.7440	12.5134**	67.0279**	5.6069*
leis	0.0136	0.0721	0.9321	10.8578	7.9370**	46.2256**	8.5852**
papa	0.0109	0.0689	0.4158	5.9602	3.5408**	25.3746**	9.4226**
stor	0.0125	0.0713	1.0216	9.0783	8.6985**	38.6494**	9.6797**
text	0.0111	0.0677	0.5266	6.6148	4.4838**	28.1617**	0.2028
oils	0.0161	0.0717	1.1302	9.5875	9.6234**	40.8173**	10.8941**
i500	0.0132	0.0583	1.2042	14.9590	10.2537**	63.6856**	10.5660**
alls	0.0131	0.0591	1.2213	15.4022	10.3987**	65.5725**	10.7268**
	Returns excluding 1975 and 1987 shocks (R^*_t)						
buil	0.0114	0.0699	-0.0773	0.8532	-0.6585	3.6325**	3.9409*
elec	0.0126	0.0629	0.0613	1.1625	0.5223	4.9492**	0.5377
enge	0.0106	0.0604	-0.2817	0.6378	-2.3987**	2.7153**	3.6124
motr	0.0120	0.0720	0.0880	0.5522	0.7497	2.3508**	3.3823
bwds	0.0125	0.0599	-0.1687	1.8828	-1.4365	8.0157**	0.5821
fdmf	0.0117	0.0533	-0.2101	1.2112	-1.7886	5.1563**	2.9440
leis	0.0125	0.0639	-0.3625	1.5361	-3.0867**	6.5396**	10.8942**
papa	0.0103	0.0623	-0.2751	0.8792	-2.3426**	3.7430**	4.7916*
stor	0.0115	0.0640	0.0371	2.7118	0.3161	11.5452**	0.9582
text	0.0105	0.0614	-0.0804	0.4283	-0.6842	1.8235	0.2673
oils	0.0151	0.0634	0.1012	0.3136	0.8619	1.3350	14.9830**
i500	0.0124	0.0497	-0.3501	1.3002	-2.9811**	5.5355**	2.6151
alls	0.0123	0.0503	-0.3901	1.4294	-3.3213**	6.0853**	2.1992

Notes: Dmskew is the Davidson-MacKinnon test for skewness distributed as N(0,1)
Dmkurt is the Davidson-MacKinnon test for excess kurtosis distributed as N(0,1)
arch is a x^2 test for arch(1)
* significant at the 95% level; ** significant at the 99% level

Table 3. Variance Ratio Test Results: Data including 1975 and 1987 shocks

Returns (R_t)						
horizon (Q)		**3**	**6**	**12**	**24**	**60**
buil	$M(Q)$	0.1008	0.0498	0.0430	-0.1085	-0.2895
	$Z_1(Q)$	1.4099	0.4199	0.2391	-0.4131	-0.6836
	$Z_2(Q)$	0.9569	0.2896	0.0166	-0.0155	-0.0114
elec	$M(Q)$	0.1218	0.1574	0.1151	-0.0424	-0.1176
	$Z_1(Q)$	1.7040‡	1.3280	0.6405	-0.1614	-0.2776
	$Z_2(Q)$	1.1579	0.9511	0.0474	-0.0062	-0.0045
enge	$M(Q)$	0.1216	0.0515	-0.0645	-0.2348	-0.5023
	$Z_1(Q)$	1.7016‡	0.4347	-0.3587	-0.8936	-1.1861
	$Z_2(Q)$	1.0636	0.2917	-0.0264	-0.0350	-0.0204
motr	$M(Q)$	0.2141*	0.2282*	0.2976‡	0.3129	-0.0002
	$Z_1(Q)$	2.9956*	1.9252‡	1.6554‡	1.1909	-0.0004
	$Z_2(Q)$	2.3288*	1.5352	0.1239	0.0464	-0.0000
bwds	$M(Q)$	0.0011	-0.0222	-0.0580	-0.1557	-0.3844
	$Z_1(Q)$	0.0156	-0.1873	-0.3224	-0.5925	-0.9077
	$Z_2(Q)$	0.0114	-0.1385	-0.0206	-0.0201	-0.0152
fdmf	$M(Q)$	0.1528*	0.2003	0.1484	-0.0333	-0.2992
	$Z_1(Q)$	2.1377*	1.6899‡	0.8258	-0.1268	-0.7065
	$Z_2(Q)$	1.3105	1.1048	0.0510	-0.0047	-0.0116
leis	$M(Q)$	0.1500‡	0.2061	0.1983	0.0042	-0.3025
	$Z_1(Q)$	2.0989*	1.7388‡	1.1032	0.0160	-0.7143
	$Z_2(Q)$	1.2894	1.1096	0.0673	0.0006	-0.0122
papa	$M(Q)$	0.0044	-0.0847	-0.1292	-0.1304	0.0128
	$Z_1(Q)$	0.0615	-0.7150	-0.7188	-0.4964	0.0303
	$Z_2(Q)$	0.0424	-0.5087	-0.0535	-0.0201	0.0005
stor	$M(Q)$	-0.0061	0.0081	-0.0094	-0.1775	-0.3404
	$Z_1(Q)$	-0.0848	0.0686	-0.0521	-0.6755	-0.8039
	$Z_2(Q)$	-0.0531	0.0441	-0.0031	-0.0233	-0.0131
text	$M(Q)$	0.0522	0.0867	0.0154	-0.1568	-0.2623
	$Z_1(Q)$	0.7305	0.7311	0.0858	-0.5969	-0.6195
	$Z_2(Q)$	0.6356	0.6012	0.0065	-0.0229	-0.0102
oils	$M(Q)$	0.0173	0.0955	0.0693	-0.1857	-0.3840
	$Z_1(Q)$	0.2424	0.8054	0.3855	-0.7066	-0.9067
	$Z_2(Q)$	0.1458	0.5028	0.0283	-0.0306	-0.0149
i500	$M(Q)$	0.0901	0.1363	0.1057	-0.1042	-0.3007
	$Z_1(Q)$	1.2600	1.1503	0.5879	-0.3965	-0.7100
	$Z_2(Q)$	0.6765	0.6568	0.0363	-0.0142	-0.0117
alls	$M(Q)$	0.0998	0.1307	0.0900	-0.1430	-0.3641
	$Z_1(Q)$	1.3965	1.1027	0.5004	-0.5442	-0.8597
	$Z_2(Q)$	0.7416	0.6210	0.0306	-0.0191	-0.0143

Notes: ‡ significant at the 90% level; * significant at the 95% level

Table 4. Simulated Distribution of *M(Q)*

horizon *(Q)*	**3**	**6**	**12**	**24**	**60**
%					
1	-0.157	-0.251	-0.367	-0.500	-0.691
2.5	-0.133	-0.214	-0.315	-0.447	-0.635
5	-0.112	-0.183	-0.275	-0.395	-0.579
10	-0.089	-0.148	-0.224	-0.326	-0.501
50	-0.001	-0.005	-0.014	-0.027	-0.087
90	0.094	0.156	0.238	0.355	0.617
95	0.123	0.208	0.319	0.496	0.877
97.5	0.149	0.251	0.399	0.623	1.144
99	0.174	0.304	0.481	0.793	1.547

Notes: Based on drawings from an N(0,1) distribution with 435 observations and 10,000 replications

Table 5. Variance Ratio Test Results: Data excluding 1975 and 1987 shocks

		Returns (R^*_t)				
horizon (*Q*)		**3**	**6**	**12**	**24**	**60**
buil	$M^*(Q)$	0.1232‡	0.1440	0.2831	0.4452	0.3420
	$Z^*_1(Q)$	1.7243‡	1.2148	1.5749	1.6946‡	0.8075
	$Z^*_2(Q)$	1.5140	1.0672	0.1203	0.0668	0.0133
elec	$M^*(Q)$	0.0880	0.2030	0.3938‡	0.5320‡	0.3272
	$Z^*_1(Q)$	1.2311	1.7125‡	2.1909*	2.0249*	0.7727
	$Z^*_2(Q)$	1.2629	1.6866‡	0.1815	0.0822	0.0125
enge	$M^*(Q)$	0.1025	0.0545	0.0641	0.1855	0.1305
	$Z^*_1(Q)$	1.4342	0.4599	0.3568	0.7062	0.3083
	$Z^*_2(Q)$	1.2761	0.4099	0.0287	0.0292	0.0053
motr	$M^*(Q)$	0.2069*	0.2755*	0.4148*	0.6330*	0.6510
	$Z^*_1(Q)$	2.8941*	2.3245*	2.3073*	2.4094*	1.5373
	$Z^*_2(Q)$	2.6037*	2.0784*	0.1934	0.0969	0.0264
bwds	$M^*(Q)$	-0.0404	-0.0379	0.0874	0.3173	0.2723
	$Z^*_1(Q)$	-0.5654	-0.3198	0.4862	1.2078	0.6430
	$Z^*_2(Q)$	-0.5043	-0.2790	0.0386	0.0469	0.0105
fdmf	$M^*(Q)$	0.0772	0.1587	0.3713‡	0.6082‡	0.7412
	$Z^*_1(Q)$	1.0800	1.3387	2.0655*	2.3150*	1.7503‡
	$Z^*_2(Q)$	0.9733	1.2185	0.1599	0.0894	0.0281
leis	$M^*(Q)$	0.1423‡	0.2278‡	0.4215*	0.6450*	0.5600
	$Z^*_1(Q)$	1.9906*	1.9216‡	2.3446*	2.4550*	1.3223
	$Z^*_2(Q)$	1.6039	1.5770	0.1840	0.0961	0.0224
papa	$M^*(Q)$	-0.0201	-0.1021	-0.0353	0.2461	0.8686
	$Z^*_1(Q)$	-0.2807	-0.8615	-0.1965	0.9365	2.0510*
	$Z^*_2(Q)$	-0.2466	-0.7670	-0.0161	0.0387	0.0350
stor	$M^*(Q)$	-0.0604	-0.0421	0.0845	0.2261	0.2281
	$Z^*_1(Q)$	-0.8453	-0.3550	0.4703	0.8606	0.5386
	$Z^*_2(Q)$	-0.7426	-0.3085	0.0353	0.0327	0.0086
text	$M^*(Q)$	0.0312	0.1298	0.1924	0.3087	0.6651
	$Z^*_1(Q)$	0.4359	1.0951	1.0703	1.1749	1.5705
	$Z^*_2(Q)$	0.4124	1.0094	0.0865	0.0481	0.0258
oils	$M^*(Q)$	-0.0115	0.0811	0.2476	0.1920	0.2354
	$Z^*_1(Q)$	-0.1605	0.6845	1.3774	0.7307	0.5559
	$Z^*_2(Q)$	-0.1382	0.6076	0.1068	0.0294	0.0091
i500	$M^*(Q)$	0.0547	0.1814	0.4366*	0.6870*	0.8953‡
	$Z^*_1(Q)$	0.7646	1.5303	2.4287*	2.6147*	2.1141*
	$Z^*_2(Q)$	0.6674	1.3029	0.1817	0.0995	0.0334
alls	$M^*(Q)$	0.0549	0.1734	0.4379*	0.6977*	0.9023‡
	$Z^*_1(Q)$	0.7684	1.4630	2.4361*	2.6553*	2.1306*
	$Z^*_2(Q)$	0.6708	1.2402	0.1807	0.1004	0.0338

Notes: ‡ significant at the 90% level; * significant at the 95% level

Table 6. Variance Ratio Test Results: Differences

Returns (R^*_t)						
horizon (Q)		**3**	**6**	**12**	**24**	**60**
buil	$M^D(Q)$	-0.0225	-0.0942*	-0.2401*	-0.5538*	-0.6315*
	$Z^D_1(Q)$	-0.3144	-0.7949	-1.3358	-2.1076	-1.4911
	$Z^D_2(Q)$	-0.5572	-0.7776	-0.1037	-0.0822	-0.0247
elec	$M^D(Q)$	0.0338	-0.0456	-0.2787*	-0.5744*	-0.4448*
	$Z^D_1(Q)$	0.4729	-0.3845	-1.5504	-2.1863	-1.0503
	$Z^D_2(Q)$	-0.1050	-0.7354	-0.1341	-0.0884	-0.0170
enge	$M^D(Q)$	0.0191	-0.0030	-0.1286‡	-0.4203*	-0.6328*
	$Z^D_1(Q)$	0.2674	-0.0252	-0.7154	-1.5998	-1.4943
	$Z^D_2(Q)$	-0.2125	-0.1182	-0.0552	-0.0642	-0.0257
motr	$M^D(Q)$	0.0072	-0.0473	-0.1172	-0.3201*	-0.6512*
	$Z^D_1(Q)$	0.1014	-0.3994	-0.6520	-1.2184	-1.5377
	$Z^D_2(Q)$	-0.2749	-0.5432	-0.0695	-0.0505	-0.0264
bwds	$M^D(Q)$	0.0415	0.0157	-0.1454*	-0.4730*	-0.6567*
	$Z^D_1(Q)$	0.5810	0.1326	-0.8087	-1.8003	-1.5507
	$Z^D_2(Q)$	0.5158	0.1405	-0.0592	-0.0670	-0.0257
fdmf	$M^D(Q)$	0.0756*	0.0416	-0.2228*	-0.6416*	-1.0404*
	$Z^D_1(Q)$	1.0578	0.3512	-1.2396	-2.4419‡	-2.4568‡
	$Z^D_2(Q)$	0.3372	-0.1136	-0.1088	-0.0941	-0.0398
leis	$M^D(Q)$	0.0077	-0.0217	-0.2231*	-0.6408*	-0.8625*
	$Z^D_1(Q)$	0.1084	-0.1828	-1.2414	-2.4390‡	-2.0367
	$Z^D_2(Q)$	-0.3145	-0.4674	-0.1167	-0.0955	-0.0346
papa	$M^D(Q)$	0.0245	0.0174	-0.0939	-0.3765*	-0.8557*
	$Z^D_1(Q)$	0.3421	0.1465	-0.5223	-1.4329	-2.0207
	$Z^D_2(Q)$	0.2891	0.2583	-0.0374	-0.0588	-0.0345
stor	$M^D(Q)$	0.0544*	0.0502	-0.0939	-0.4036*	-0.5685*
	$Z^D_1(Q)$	0.7605	0.4236	-0.5224	-1.5362	-1.3425
	$Z^D_2(Q)$	0.6895	0.3526	-0.0385	-0.0559	-0.0217
text	$M^D(Q)$	0.0211	-0.0431	-0.1770*	-0.4655*	-0.9274*
	$Z^D_1(Q)$	0.2947	-0.3639	-0.9846	-1.7717	-2.1900
	$Z^D_2(Q)$	0.2232	-0.4083	-0.0800	-0.0710	-0.0360
oils	$M^D(Q)$	0.0288	0.0143	-0.1783*	-0.3777*	-0.6194*
	$Z^D_1(Q)$	0.4028	0.1209	-0.9919	-1.4374	-1.4625
	$Z^D_2(Q)$	0.2840	-0.1048	-0.0785	-0.0600	-0.0241
i500	$M^D(Q)$	0.0354	-0.0450	-0.3309*	-0.7912*	-1.1959*
	$Z^D_1(Q)$	0.4954	-0.3801	-1.8409	-3.0113*	-2.8241*
	$Z^D_2(Q)$	0.0091	-0.6461	-0.1454	-0.1137	-0.0452
alls	$M^D(Q)$	0.0449	-0.0427	-0.3479*	-0.8406*	-1.2663*
	$Z^D_1(Q)$	0.6281	-0.3603	-1.9357	-3.1995*	-2.9903*
	$Z^D_2(Q)$	0.0708	-0.6191	-0.1501	-0.1195	-0.0481

Notes: ‡ significant at the 90% level; * significant at the 95% level

Table 7. Simulated Distribution of $M^D(Q) = M_1(Q)\text{-}M_2(Q)$

horizon (Q)	3	6	12	24	60
%					
1	-0.066	-0.107	-0.168	-0.259	-0.461
2.5	-0.055	-0.09	-0.143	-0.213	-0.371
5	-0.046	-0.077	-0.12	-0.177	-0.295
10	-0.036	-0.06	-0.09	-0.132	-0.214
50	0.0001	-0.0004	-0.001	-0.001	-0.002
90	0.036	0.059	0.089	0.321	0.217
95	0.045	0.076	0.115	0.172	0.282
97.5	0.054	0.09	0.14	0.207	0.354
99	0.064	0.107	0.167	0.251	0.448

Notes: Based on drawings from a N(0,1) distribution with 435 observations and 10,000 replications

Significance levels for $N(0,2^{0.5})$

$P(Z^D_i(Q)<k)$	0.50	0.90	0.95	0.975	0.99
k	0.0	1.81	2.33	2.77	3.31

Table 8 Modified Rescaled Range Test Results

h	3	6	12	24
Returns including 1975 and 1987 shocks (R_t)				
buil	1.7023	1.6100	1.6523	1.6809
elec	1.5740	1.4817	1.4678	1.4853
enge	1.3801	1.2893	1.3187	1.3472
motr	1.6384	1.4600	1.4661	1.4704
bwds	1.4416	1.4396	1.4380	1.4581
fdmf	1.5739	1.4310	1.4297	1.4611
leis	1.5460	1.4097	1.3950	1.4029
papa	1.7657	1.7404	1.7803	1.8148
stor	1.5495	1.5434	1.5481	1.5526
text	1.3850	1.3299	1.3115	1.3251
oils	1.3216	1.3006	1.2706	1.2761
i500	1.6784	1.5883	1.5807	1.5986
alls	1.6113	1.5173	1.5168	1.5351
Returns excluding 1975 and 1987 shocks (R^*_t)				
buil	1.7002	1.5905	1.5778	1.5753
elec	1.4030	1.3320	1.2817	1.2754
enge	1.4801	1.3912	1.4021	1.4161
motr	1.7322	1.5379	1.5184	1.5120
bwds	1.5431	1.5764	1.5448	1.5433
fdmf	1.6203	1.5359	1.4898	1.4882
leis	1.5859	1.4549	1.4124	1.3973
papa	1.9493	1.9557	1.9638	1.9727
stor	1.6089	1.6721	1.6456	1.6222
text	1.5150	1.4625	1.4020	1.3914
oils	1.5627	1.5666	1.5098	1.4937
i500	1.6789	1.6141	1.5479	1.5287
alls	1.7158	1.6488	1.5813	1.5607

Significance levels for MRS, from Lo (1991) table 6.2

P(MRS<k)	0.005	0.025	0.05	0.10	0.90	0.95	0.975	0.995
k	0.721	0.809	0.861	0.927	1.620	1.747	1.862	2.098

Chart 1: FTA500 - Index of Industrial Ordinary Shares 1962-1998

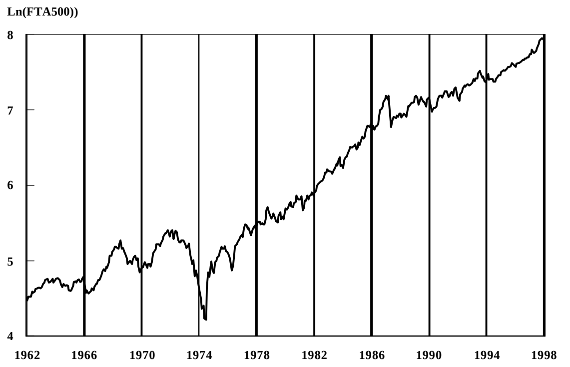


Chart 2: One-month Total Return on the FTA500 1962-1998

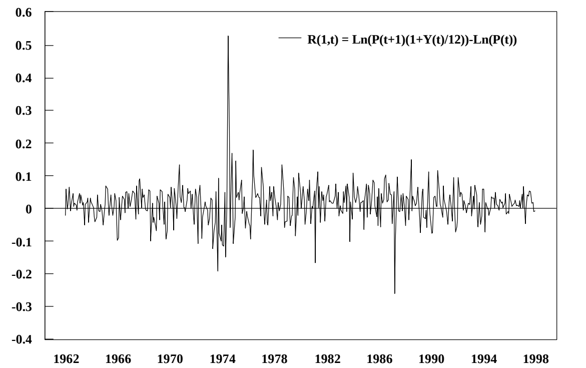


Chart 3: 3-month Total Return on the FTA500 1962-1998

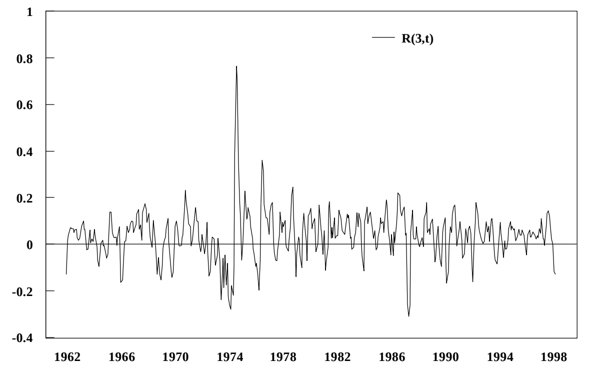


Chart 4: 6-month Total Return on the FTA500 1962-1998

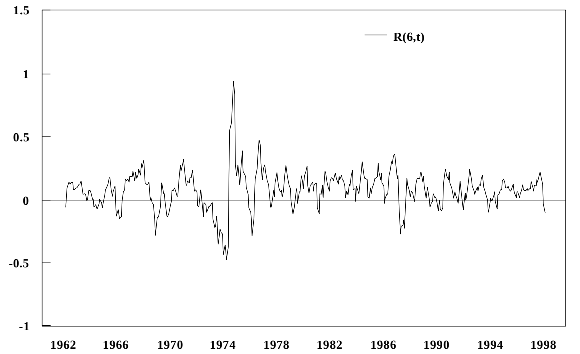


Chart 5: 12-month Total Return on the FTA500 1962-1998

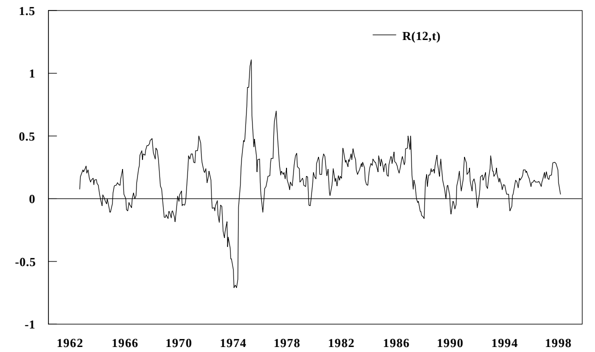


Chart 6: 24-month Total Return on the FTA500 1962-1998

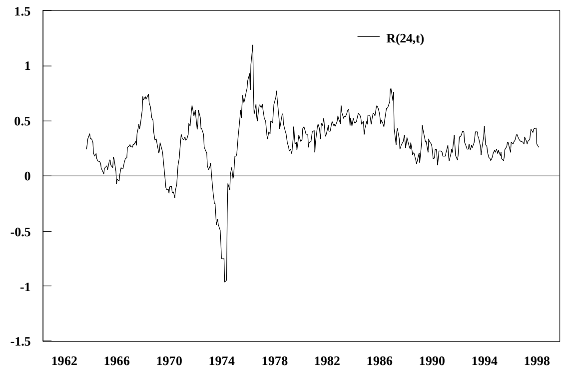
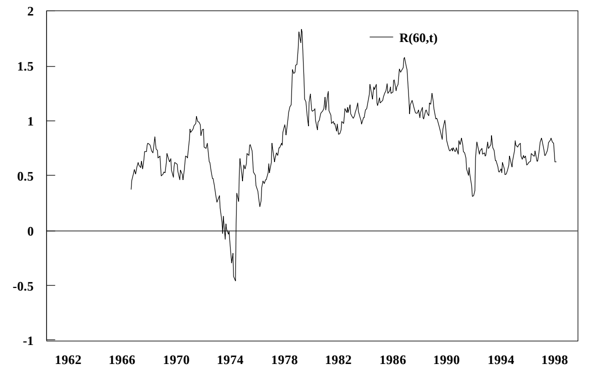


Chart 7: 60-month Total Return on the FTA500 1962-1998



[1] This result could be related to that of Fama and French (1988a) who found evidence of a significant change in firms' dividend policy as between the inter-war and post-war years, a change which may be reflected in corresponding changes in stock price behaviour.

[2] As we discuss in section 2, Lo and MacKinlay pointed out that the distribution of the VR statistic tends to be skewed, even in the relatively large samples which are typical of stock market datasets, although it does have a standard limiting distribution. Richardson and Stock emphasized the need to simulate the empirical distribution which corresponds to the sample size actually used by the investigator. This was not done by Frennberg and Hansson, or by MacDonald and Power, or by Claessens, Dasgupta, and Glen.

[3] Stock market data from 1976 were extracted from DATASTREAM. Data prior to 1976, and some corrections to the DATASTREAM data were provided by The Institute of Actuaries. Data for bills were taken from Green Maggioni and Bowen (1992). Mills (1991) argued that pre-1965 data are tainted by the existence at the time of dividend controls. This is not a view we share. Actually, dividend controls were in existence in the UK for most of the 1960s and through the early part of the 1970s. Moreover, even if a firm is constrained in the dividends it can pay, theory would suggest that its stock price would adjust to make the total return equal to that required by investors in a competitive market.

[4] Of course, it is more difficult to incorporate dividends or retail prices in datasets of higher frequency than monthly.

[5] The exposition in this section follows Lo and Mackinley (1988, 1989).

[6] Plots of the all-share index and of the industrial groups in this study produce broadly similar pictures, in the relevant respects.

[7] The notation for the shock-purged VR and MRS statistics is analagous; ie. $M^*(Q)$, $Z^*_1(Q)$, $Z^*_2(Q)$, and MRS^*.

[8] Qualitatively similar results were found for X_t, and G_t.

[9] Simulations of $M^*(Q)$ were based on drawings from an N(0,1) distribution, with 435 observations and 10,000 replications

[10] This is a two-tailed test.