Further evidence on the predictability of UK stock returns

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NB
The results contained in this paper are provisional and should not be quoted without the written consent of the first-named author.

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Abstract

This paper presents evidence on the predictability of UK stock returns using a newly constructed database of companies in the FTSE-Allshare index towards the beginning of 1998. The tests used are autocorrelations at various lags and variance ratios for several aggregations of base observations. The evidence is consistent with that published for US stock returns, namely that daily stock returns contain a strong element of predictability. Moreover the results are largely robust to the Chow and Denning critique of the interpretation of the critical values of the test statistics used to interpret the variance ratios. However, it is suggested that the fact that daily stock returns contain an element of predictability is of little practical significance for the process of investment management. (JEL C4,C8,G1)

Key words: UK daily stock returns, autocorrelations, variance ratios.

1 Introduction

The proposition that stock returns are predictable is gaining widespread currency.[1] In recent research, the first-named author has argued that it is possible to model the UK stock market as a whole and that model-based market forecasts can contribute to a quantitative approach to risk management (Lovatt and Parikh 2000, Lovatt 2000). In this paper, therefore, we begin the task of developing a quantitative risk-management system which may be applied to individual stocks grouped into portfolios. The first thing that we want to know is whether established tests of predictability may be applied to portfolios of UK stocks for recent years. To this end, we have built a database of daily split-adjusted closing prices, dividend yields, and market values for every stock in the FTSE All-share towards the beginning of 1998. The database itself covers the period 01/10/92-20/3/98. The data relates to a total of 871 companies. The tests are autocorrelations at various lags and variance ratios using several aggregation periods on continuously compounded daily returns measured simply as daily price changes of the sample of companies grouped randomly into 10 portfolios and for the sample as a whole.[2] The evidence is consistent with research already published for US stocks, namely that stock returns contain a strong element of predictability. (See in particular, Campbell, Lo, and MacKinlay, (CLM) 1997 tables 2.5 p. 69 and 2.6, p. 71).

2 Theory

The random walk model may be written simply as,

$$p_t = \mu + p_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim \text{IID}N(0, \sigma^2) \tag{1}$$

In (1), p_t is the natural logarithm of the stock price. Equation (1) states that the first difference of the natural logarithm of the price (one plus the capital gain) varies randomly around a constant expected value. In this equation, continuously compounded returns (ignoring the dividend) are IID normal variates with mean μ and variance σ^2.

As CLM point out, one can relax the assumptions of this model in two ways. First, we can assume that the incremental deviations in the first differences of the logarithms of the prices around the mean return are independently but not identically distributed. CLM refer to this as the random walk 2 model. Second, we can go further and assume that the increments are dependent but uncorrelated. This version of the random walk model is the one which is most often tested in practice. CLM refer to this as the random walk 3 model. It implies that $\text{Cov}[\varepsilon_t, \varepsilon_{t-k}] = 0$ for all $k \neq 0$ but that $\text{Cov}[\varepsilon_{\text{t}}^2, \varepsilon_{t-k}^2] \neq 0$ for some $k \neq 0$.

The standard approach to testing this weaker version of the random walk model is to estimate an autocorrelation function at various lags. Denoting the continuously compounded return as, $r_t = p_t - p_{t-1}$ we have,

$$\rho(k) = \frac{\text{Cov}[r_t, r_{t+k}]}{\text{Var}[r_t]} = \frac{\gamma(k)}{\gamma(0)} \qquad (2)$$

assuming that the return series is covariance stationary. The statistic $Q'_m \equiv T(T+2)\sum_{k=1}^{m}\frac{\rho^2(k)}{T-k}$ is used to test the joint significance of the m autocorrelations and is distributed as χ_m^2 (See footnote 3).

The second test that is most commonly used to test for predictability is the variance ratio.[4] This statistic makes use of the fact that, where logarithmic returns are IID, the variance of $r_t + r_{t-1}$ must be twice the variance of r_t. That is, under the random walk null, the ratio of the variance of the two-period continuously compounded return to twice the variance of the one-period return should equal one,

$$\mathrm{VR}(2) = \frac{\mathrm{Var}[r_t(2)]}{2\mathrm{Var}[r_t]} = \frac{\mathrm{Var}[r_t + r_{t-1}]}{2\mathrm{Var}[r_t]} = 1 + \rho(1) = 1 \tag{3}$$

More generally, CLM show that, under the same null,

$$\mathrm{VR}(q) \equiv \frac{\mathrm{Var}[r_t(q)]}{q.\mathrm{Var}[r_t]} = 1 + 2\sum_{k=1}^{q-1}(1 - \frac{k}{q})\rho(k) = 1 \tag{4}$$

where $r_t(q) \equiv r_t + r_{t-1} + ... + r_{t-(q-1)}$.

The following estimators are for a sample of $nq+1$ logarithmic prices, use overlapping $q-\text{period}$ returns in defining the numerator in the variance ratio and are corrected for bias[5],

$$\hat{\mu} = \frac{1}{nq}\sum_{k=1}^{nq}(p_k - p_{k-1}) = \frac{1}{nq}(p_{nq} - p_0) \tag{5}$$

$$\bar{\sigma}_a^2 = \frac{1}{nq-1}\sum_{k=1}^{nq}(p_k - p_{k-1} - \hat{\mu})^2 \tag{6}$$

$$\overline{\sigma}_c^2(q) = \frac{1}{m}\sum_{k=q}^{nq}(p_k - p_{k-q} - q\widehat{\mu})^2 \tag{7}$$

$$m = q(nq - q + 1)(1 - \frac{q}{nq}) \tag{8}$$

$$\overline{\text{VR}}(q) \equiv \frac{\overline{\sigma}_c^2(q)}{\overline{\sigma}_a^2} \tag{9}$$

Even under the uncorrelated increments version of the random walk model, the variance ratio will approach unity but an adequate test must clearly deal with the presence of heteroscedasticity since a rejection of the null for this reason would be of no interest. Lo and MacKinlay (1988) proposed the following heteroscedasticity-consistent test statistic,

$$\widehat{\delta}_k = \frac{nq\sum_{j=k+1}^{nq}(p_j - p_{j-1} - \widehat{\mu})^2(p_{j-k} - p_{j-k-1} - \widehat{\mu})^2}{\left[\sum_{j=1}^{nq}(p_j - p_{j-1} - \widehat{\mu})^2\right]^2} \tag{10}$$

$$\widehat{\theta}(q) \equiv 4\sum_{k=1}^{q-1}(1 - \frac{k}{q})^2\,\widehat{\delta}_k \tag{11}$$

$$\psi^*(q) = \frac{\sqrt{nq}(VR(q) - 1)}{\sqrt{\widehat{\theta}(q)}} \xrightarrow[a]{} N(0,1) \tag{12}$$

Chow and Denning (C&D, 1993) argued that the Lo and Mackinlay approach is appropriate for testing a variance ratio corresponding to a specific aggregation value, q, by comparing the test statistic to the standard normal critical value. However, since the random walk hypothesis requires that the variance ratios for all aggregation intervals selected should equal one, an obvious approach to testing the null hypothesis is the multiple comparison of all selected variance ratio estimates with unity. The suggested approach makes use of the largest absolute value of the test statistics, $\psi^*(q)$.

$$\psi^*_{\max} = \max_{1 \le i \le m} \left| \psi^*(q_i \right| \qquad (13)$$

C & D show, in their Lemma 1, that the confidence interval of at least $100(1-\alpha)\%$ for the extreme statistic $\psi^*_{\max}$ can be defined as,

$$\psi^*_{\max} \pm \text{SMM}(\alpha; m; \infty) \qquad (14)$$

$\text{SMM}(\alpha; m; \infty)$ is the asymptotic critical value of the $\alpha-\text{point}$ of the studentized maximum modulus distribution with parameter m and ∞ degrees of freedom.[6] It can also be calculated from the conventional standard normal distribution where $\text{SMM}(\alpha; m; \infty) = Z_{\alpha^+/2}$ where $\alpha^+ = 1-(1-\alpha)^{\frac{1}{m}}$. One can, therefore, proceed by simply comparing the Lo and MacKinlay test statistics for the m different values of q with the SMM critical value.

3 The data

The sample companies were randomly allocated into 10 portfolios of equal size and both equally and value weighted daily returns were calculated for all 10 portfolios and for the sample as a whole.[7] Table 1 contains summary statistics for the daily arithmetic returns of all

10 portfolios and for the sample as a whole. In general, the value-weighted portfolios have higher standard deviations than the equally-weighted ones. Note also that the skewness and excess kurtosis statistics, when multiplied respectively by $\sqrt{\frac{nq}{6}}$ and $\sqrt{\frac{nq}{24}}$ are asymptotically distributed as $N(0,1)$ under the null hypothesis of normality implying a rejection of the normality assumption in most cases.[8]

4 Autocorrelations

Tables 2 and 3 show the autocorrelations of daily, continuously compounded returns for both the ten equally- and value-weighted portfolios and for all companies together with the corresponding Q-statistics. The equally-weighted autocorrelations are typically higher than the value-weighted ones and the Q-statistics typically reject the random walk null in both cases. This evidence is entirely consistent with that published by CLM for the US market.[9]

5 Variance Ratios

Tables 4 and 5 contain the estimated variance ratios for the same data together with the associated statistics $\psi^*(q)$. Note that the VR(2) should be equal to 1 plus the autocorrelation coefficient at lag 1 and this is the case. For the equally-weighted portfolio the VR is always greater than 1 and the heteroscedasticity-robust test statistic consistently rejects the random walk null hypothesis when the ratios are considered one at a time. The 5 % SMM critical value for the joint significance of the ratios is 2.632. Again this test decisively rejects the random walk null for all variance ratios calculated from equally-weighted returns.

The results from the value-weighted returns are less decisive but are again consistent with the results published by CLM. The results for all companies are all greater than 1 but in one case $(q = 10)$ the SMM critical value does not reject the random walk null. This is also the case with a number of the individual portfolio statistics.

6 Conclusion

The evidence of this paper is that, using conventional tests of predictability, daily UK stock returns do show some evidence of predictability. This result is interesting in that it confirms the results of previous research. However, it remains to be seen if this evidence of predictability is sufficiently robust to enable us to construct an equity-risk management system for the quantitative management of individual stocks grouped into portfolios.

Footnotes

[1] Probably the most extensive treatment currently available is Campbell, Lo, and MacKinlay (1997) who provide extensive references. See especially chapter 2. Important UK references include MacDonald and Power (1991, 1992, and 1993), Mills (1991), and Fraser and Power (1992).

[2] The results reported in tables 2 to 5 below use continuously compounded returns defined as the natural logarithm of one plus the nominal arithmetic return divided by 100 while the summary statistics of table 1 are based on arithmetic returns. In practice, it makes little difference to the results reported in tables 1 to 3 whether arithmetic or logarithmic returns are used but variance ratios normally make use of the additive properties of logarithmic returns. Also, whereas the dividend yield represents approximately one third of the total annual real return of the UK stock market as a whole, its impact on daily nominal returns is negligible.

[3] The original Q-statistic, $Q_m \equiv T\sum_{k=1}^{m}\rho^2(k)$, is attributable to Box and Pierce(1970). TSP calculates the Ljung-Box statistic given in the text. This provides a finite sample correction to the Q-statistic. (Ljung and Box, 1978).

[4] The variance ratios and associated test statistics reported in this paper were estimated using a FORTRAN algorithm. They provide independent confirmation of the autocorrelations estimated by TSP.

[5] The notation follows that of CLM.

[6] The SMM table can be found in Hahn and Hendrickson (1971).

[7] Nine of the ten portfolios contained 87 stocks while the tenth, selected at random, contained 88. Returns for each day and for each portfolio are based on companies reporting prices for the relevant two days. In practice, therefore, the number of companies determining the daily portfolio return does vary over time.

[8] This conclusion also applies to the continuously compounded returns.

[9] The daily autocorrelation at one lag for the CRSP value-weighted index is .176 or 17.6% while that for the equal-weighted index is .35 or 35% for the sample as a whole (03/07/62-30/12/94). For the more recent sub-period (30/10/78-30/12/94), CLM report autocorrelations of .108 and .262 respectively. The results reported in the present paper are almost identical.

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	Mean daily return	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
Portfolio 1						
Equally weighted	0.071	0.427	-4.295	2.605	-0.784	11.034
Value weighted	0.071	0.785	-3.870	3.727	0.004	1.610
Portfolio 2						
Equally weighted	0.078	0.426	-4.582	2.919	-1.054	14.535
Value weighted	0.075	0.720	-4.339	3.758	-0.268	2.312
Portfolio 3						
Equally weighted	0.078	0.395	-4.374	2.494	-1.100	15.414
Value weighted	0.071	0.785	-3.464	3.243	-0.133	0.750
Portfolio 4						
Equally weighted	0.077	0.446	-4.709	3.018	-0.800	13.407
Value weighted	0.040	0.675	-3.896	3.095	-0.143	2.178
Porfolio 5						
Equally weighted	0.078	0.444	-4.938	2.845	-1.132	14.979
Value weighted	0.063	0.663	-3.501	3.034	-0.226	1.575
Portfolio 6						
Equally weighted	0.076	0.431	-4.589	2.999	-0.553	16.082
Value weighted	0.067	0.848	-5.468	8.751	0.517	9.473
Portfolio 7						
Equally weighted	0.079	0.394	-4.077	2.563	-0.797	12.367
Value weighted	0.090	0.779	-3.827	3.879	-0.239	1.892
Portfolio 8						
Equally weighted	0.079	0.447	-5.116	2.921	-0.970	16.097
Value weighted	0.070	0.706	-3.839	3.263	-0.166	1.874
Portfolio 9						
Equally weighted	0.070	0.392	-4.520	2.495	-0.993	16.848
Value weighted	0.064	0.704	-3.134	3.177	-0.195	1.474
Portfolio 10						
Equally weighted	0.075	0.407	-4.429	2.643	-0.883	14.182
Value weighted	0.073	0.724	-3.888	2.852	-0.108	1.568
All companies						
Equally weighted	0.076	0.385	-4.562	2.749	-1.324	19.899
Value weighted	0.069	0.643	-3.658	2.820	-0.251	1.884

Table 1 Summary statistics for 10 randomly allocated portfolios and for all companies for stocks in the FTSE Allshare, daily arithmetic returns, 2/10/92-20/3/98 (1426 observations)

Autocorrelations (Q statistics in brackets)

Number of lags	1	2	3	4	5	10	20
Equally-weighted returns							
Portfolio 1	0.254	0.178	0.163	0.075	0.077	0.068	0.058
	(92.2)	(137.0)	(175.0)	(184.0)	(192.0)	(245.0)	(297.0)
Portfolio 2	0.203	0.126	0.099	0.048	-0.005	0.052	0.068
	(58.7)	(81.2)	(95.1)	(98.4)	(98.4)	(124.0)	(161.0)
Portfolio 3	0.251	0.184	0.135	0.085	0.056	0.078	0.039
	(89.8)	(138.0)	(164.0)	(174.0)	(179.0)	(234.0)	(270.0)
Portfolio 4	0.204	0.171	0.126	0.026	0.044	0.046	0.031
	(59.2)	(101.0)	(124.0)	(125.0)	(127.0)	(161.0)	(180.0)
Portfolio 5	0.204	0.138	0.140	0.064	0.025	0.051	0.037
	(59.6)	(87.0)	(115.0)	(121.0)	(122.0)	(160.0)	(186.0)
Portfolio 6	0.235	0.150	0.116	0.050	0.049	0.064	0.063
	(78.8)	(111.0)	(130.0)	(134.0)	(137.0)	(185.0)	(222.0)
Portfolio 7	0.226	0.154	0.144	0.027	0.041	0.074	0.061
	(72.8)	(107.0)	(136.0)	(138.0)	(140.0)	(189.0)	(225.0)
Portfolio 8	0.219	0.153	0.118	0.023	0.005	0.057	0.087
	(68.5)	(102.0)	(122.0)	(123.0)	(123.0)	(163.0)	(207.0)
Portfolio 9	0.234	0.200	0.152	0.118	0.054	0.101	0.074
	(78.4)	(136.0)	(169.0)	(189.0)	(193.0)	(265.0)	(328.0)
Portfolio 10	0.210	0.145	0.140	0.066	0.052	0.071	0.037
	(63.2)	(93.1)	(121.0)	(127.0)	(131.0)	(169.0)	(213.0)
All companies	0.243	0.184	0.154	0.068	0.047	0.078	0.065
	(84.6)	(133.0)	(167.0)	(174.0)	(177.0)	(239.0)	(289.0)

Table 2 Auto-correlations of continuously compounded daily returns at various lags for 10 randomly sorted portfolios and for all companies, 2/10/92 - 20/3/98 (1426 obs.) - equally-weighted returns.

Autocorrelations (Q statistics in brackets)

Number of lags	1	2	3	4	5	10	20
	Value-weighted returns						
Portfolio 1	0.090	-0.001	-0.025	-0.034	-0.033	-0.004	0.053
	(11.5)	(11.5)	(12.4)	(14.1)	(15.6)	(21.3)	(38.9)
Portfolio 2	0.128	0.020	-0.014	-0.063	-0.077	-0.002	0.027
	(23.4)	(24.0)	(24.3)	(29.9)	(38.3)	(45.8)	(55.8)
Portfolio 3	0.116	0.012	0.016	-0.020	-0.061	-0.001	0.020
	(19.1)	(19.3)	(19.7)	(20.3)	(25.6)	(29.0)	(33.8)
Portfolio 4	0.087	0.053	0.030	-0.053	-0.026	-0.004	-0.012
	(10.7)	(14.7)	(16.0)	(20.1)	(21.0)	(31.0)	(41.5)
Portfolio 5	0.116	0.027	-0.003	-0.037	-0.009	-0.008	0.031
	(19.1)	(20.2)	(20.2)	(22.1)	(22.2)	(26.9)	(36.8)
Portfolio 6	0.054	0.016	-0.010	-0.009	-0.057	0.021	0.031
	(4.16)	(4.52)	(4.67)	(4.79)	(9.37)	(18.8)	(34.9)
Portfolio 7	0.099	0.032	0.041	-0.011	-0.024	0.026	-0.006
	(14.1)	(15.6)	(18.0)	(18.2)	(19.0)	(24.7)	(38.8)
Portfolio 8	0.102	0.035	-0.007	-0.049	-0.058	-0.048	0.063
	(14.8)	(16.5)	(16.6)	(20.0)	(24.8)	(35.2)	(48.7)
Portfolio 9	0.124	0.032	0.026	0.007	-0.019	0.005	0.068
	(22.1)	(23.6)	(24.5)	(24.6)	(25.1)	(26.0)	(38.3)
Portfolio 10	0.115	-0.006	-0.007	-0.013	-0.051	-0.008	-0.001
	(18.8)	(18.9)	(18.9)	(19.2)	(22.9)	(36.0)	(47.9)
All companies	0.106	0.029	0.008	-0.034	-0.055	-0.004	0.040
	(16.0)	(17.2)	(17.3)	(18.9)	(23.2)	(32.3)	(45.6)

Table 3 Autocorrelations of continuously compounded daily returns at various lags for 10 randomly sorted portfolios and for all companies, 2/10/92 - 20/3/98 (1426 obs.) - value-weighted returns.

	Number (q) of base observations aggregated to form variance ratio					
	2	3	4	5	10	20
	Equally weighted returns					
Portfolio 1	1.26	1.45	1.63	1.77	2.29	3.08
	(4.45)	(7.32)	(9.76)	(11.68)	(18.96)	(30.14)
Portfolio 2	1.20	1.35	1.47	1.56	1.84	2.39
	(3.18)	(5.09)	(6.59)	(7.78)	(11.25)	(18.48)
Portfolio 3	1.25	1.45	1.61	1.75	2.26	3.06
	(4.05)	(6.78)	(8.90)	(10.73)	(17.54)	(28.27)
Portfolio 4	1.20	1.38	1.54	1.64	2.03	2.61
	(3.15)	(5.49)	(7.36)	(8.65)	(13.52)	(20.86)
Portfolio 5	1.21	1.36	1.51	1.62	2.02	2.60
	(3.26)	(5.32)	(7.22)	(8.75)	(14.07)	(21.68)
Portfolio 6	1.24	1.40	1.55	1.66	2.08	2.80
	(3.55)	(5.77)	(7.50)	(8.87)	(14.33)	(23.44)
Portfolio 7	1.23	1.40	1.56	1.67	2.08	2.74
	(3.77)	(6.25)	(8.36)	(9.80)	(15.39)	(24.45)
Portfolio 8	1.22	1.39	1.53	1.63	1.98	2.63
	(3.41)	(5.69)	(7.49)	(8.73)	(13.23)	(21.65)
Portfolio 9	1.24	1.44	1.63	1.78	2.35	3.29
	(3.67)	(6.55)	(8.97)	(11.06)	(18.58)	(30.86)
Portfolio 10	1.21	1.37	1.52	1.64	2.05	2.76
	(3.30)	(5.42)	(7.33)	(8.87)	(14.29)	(23.47)
All companies	1.24	1.44	1.62	1.75	2.25	3.07
	(3.37)	(5.75)	(7.74)	(9.32)	(15.13)	(24.76)

Table 4: Variance ratios for continuously compounded daily returns at various base aggregations for 10 randomly sorted portfolios and for all companies, 2/10/92-20/3/98 equally weighted returns

Notes: The heteroscedastic-robust test statistic of equation 12 is reported in brackets

	Number (q) of base observations aggregated to form variance ratio					
	2	3	4	5	10	20
	Value weighted returns					
Portfolio 1	1.09	1.11	1.12	1.10	1.00	0.97
	(3.04)	(3.18)	(2.94)	(2.50)	(0.02)	(-0.56)
Portfolio 2	1.13	1.18	1.19	1.18	1.07	1.07
	(4.14)	(4.75)	(4.85)	(4.38)	(1.49)	(1.61)
Portfolio 3	1.12	1.16	1.18	1.19	1.14	1.13
	(4.31)	(4.68)	(5.04)	(5.08)	(3.39)	(3.02)
Portfolio 4	1.09	1.14	1.19	1.20	1.18	1.21
	(2.28)	(3.25)	(4.02)	(4.09)	(3.48)	(3.95)
Portfolio 5	1.12	1.16	1.19	1.19	1.20	1.20
	(3.57)	(4.28)	(4.57)	(4.39)	(4.31)	(4.24)
Portfolio 6	1.05	1.08	1.09	1.09	0.97	0.95
	(1.66)	(1.98)	(2.11)	(2.11)	(-0.66)	(-1.12)
Portfolio 7	1.10	1.15	1.20	1.23	1.26	1.41
	(3.16)	(3.95)	(4.74)	(5.16)	(5.58)	(8.39)
Portfolio 8	1.10	1.15	1.17	1.17	1.07	1.01
	(2.78)	(3.57)	(3.85)	(3.65)	(1.41)	(0.24)
Portfolio 9	1.13	1.18	1.23	1.26	1.28	1.32
	(4.24)	(5.14)	(5.90)	(6.45)	(6.48)	(7.06)
Portfolio 10	1.12	1.14	1.15	1.16	1.06	0.96
	(3.62)	(3.68)	(3.74)	(3.71)	(1.27)	(-0.82)
All companies	1.11	1.15	1.18	1.19	1.12	1.13
	(3.36)	(3.96)	(4.37)	(4.33)	(2.55)	(2.79)

Table 5: Variance ratios for continuously compounded daily returns at various base aggregations for 10 randomly sorted portfolios and for all companies, 2/10/92-20/3/98 value weighted returns

Notes The heteroscedastic-robust test statistic of equation 12 is reported in brackets