reports the mean square forecast errors for the naïve forecasts of the martingale model, where forecast earnings growth is zero, and the sub-martingale model, where forecast earnings growth is the historical economy wide average earnings growth rate.

The accuracy of analysts' long run earnings growth forecasts is extremely low. In the pooled sample, the mean square forecast error for analysts is 7.15%. For the martingale model, the mean square error is 6.63%, while for the sub-martingale model, it is marginally lower at 6.60%. On average, therefore, a superior forecast of long run earnings growth for individual companies can be obtained simply by assuming that average annual earnings growth will be zero. This is a strong indictment of the accuracy of analysts' long run forecasts, and in view of the additional information available to analysts, is surprising. It also contrasts with the evidence for shorter horizon forecasts where analysts appear to have some advantage over time series models. Furthermore, the alternative models used here are relatively simple. If in fact earnings are stationary, then it is likely that a yet superior forecast could be obtained from an estimated time series model for each firm, and so the relative inferiority of analysts' forecasts is probably understated here.

Turning to the annual samples, the martingale model generates superior forecasts in seven out of eleven years, while the sub-martingale model generates forecasts that are superior to analysts' forecast in nine of the eleven years, and superior to the forecasts of the martingale model in ten out of eleven years. This suggests that one can improve on the zero growth forecast of the martingale model by using the historical economy average earnings growth rate to predict subsequent growth for individual firms. However, the improvement is only marginal, reflecting both considerable variation in average earnings growth between years and considerable dispersion in earnings growth rates across the economy. The time-series pattern of forecast errors suggests that analyst inferiority is not caused by just one or two outlying years. Nor does it suggest that there is any improvement in the accuracy of analysts' forecasts over the sample period, either relative to the forecasts of the martingale and sub-martingale models, or in absolute terms. The (unweighted) average mean square forecast error for the first five years in the sample is 7.02%, while in the last five years it is 7.28%. This is in contrast with evidence reported elsewhere that analyst accuracy has increased over time (see Brown, 1997).

(ii) Forecast Bias

Panel B of Table 1 reports the mean forecast error for analysts' forecasts of long run earnings growth, given by (3), and its standard error. In the pooled sample, the mean forecast error is negative indicating that analysts' long run earnings growth forecasts are over-optimistic. The mean forecast error is very significant both in statistical and economic terms. On average, forecast growth exceeds actual growth by about seven percent per annum. Over-optimism in long run earnings growth forecasts is consistent with evidence reported for analysts' shorter horizon earnings forecasts (see, for instance, Fried and Givoly, 1982; Brown et al., 1985; and O'Brien, 1988). It is also consistent with international evidence on analysts short run and interim forecasts (see Capstaff et al., 1995 and 1998).

The mean forecast error is also negative in each individual year, and significantly negative in all but the last, ranging from 1.50% to 11.82% per annum. This is in contrast with analysts' shorter horizon forecasts where the direction of the reported bias displays considerable year to year variation (see, for instance, Givoly, 1985). It is again notable that the degree of over-optimism has not diminished significantly over time. The (unweighted) mean forecast error for the first five years of the sample is −6.99%, while for the last five years it is −7.20%. It is of course possible that the last year in the sample, where the mean forecast error is less than two percent, marks the start of a reduction in analyst over-optimism. Whether this is borne out by future studies will be of considerable interest.

(iii) Forecast Efficiency

Panel A of Table 2 presents the results of regression (4). The efficiency condition is very strongly rejected for analysts' long run earnings growth forecasts. In the pooled sample, $\hat{\beta}$ is significantly less than unity and at 0.20, only marginally greater than zero. This is a considerably stronger rejection of efficiency than found by other authors for shorter horizon forecasts. For instance,

Table 1

Forecast Accuracy and Forecast Bias

	Panel A: Forecast Accuracy			Panel B: Forecast Bias	
	MSFE of Analysts	*MSFE of Martingale*	*MSFE of Sub-martingale*	*MFE of Analysts*	*Standard Error*
Pooled sample	7.15	6.63	6.60	−7.33	(0.31)
1982	7.34	5.15	6.41	11.39	(1.01)
1983	6.88	7.01	6.51	5.48	(1.20)
1984	6.75	7.14	6.40	4.01	(1.12)
1985	7.19	6.67	6.29	−6.61	(1.08)
1986	6.92	6.47	6.24	−7.44	(1.08)
1987	6.95	5.77	5.75	10.78	(0.99)
1988	7.38	6.32	6.40	10.20	(1.00)
1989	6.99	5.22	5.71	−11.82	(0.91)
1990	5.69	5.20	4.95	−7.40	(0.85)
1991	7.58	7.78	7.60	5.04	(0.99)
1992	8.78	9.62	9.78	1.50	(1.10)

Notes:
Panel A reports the mean square forecast error for analysts' forecasts and the forecasts of two naïve models.

The MSFE of analysts forecasts is calculated each year as $\frac{1}{N}\sum_{i=1}^{N}(g_{it} - g_{it}^{f})^2$;

the MSFE of the martingale model is calculated each year as $\frac{1}{N}\sum_{i=1}^{N}(g_{it})^2$;

the MSFE of the sub-martingale model is calculated each year as $\frac{1}{N}\sum_{i=1}^{N}(g_{it} - \bar{g}_{t-1})^2$;

where g_{it} is five year earnings growth from January year t to December year $t+4$, is forecast of g_{it} reported at April year t and $\bar{g}_{t-1}$ is the average value over all companies of five year earnings growth from January year $t-5$ to December year $t-1$. The MSFE for the pooled sample is computed over all firms and years.

Panel B reports the mean forecast error of analysts, calculated as:

$$\text{MFE} = \frac{1}{N}\sum_{i=1}^{N}(g_{it} - g_{it}^{f}),$$

and its standard error. The MFE for the pooled sample is computed over all firms and years.

DeBondt and Thaler (1990) find that while they reject the hypothesis that β is equal to unity for one and two year forecasts, their estimated parameters (0.65 for one year forecasts, 0.46 for two year forecasts) are much larger than those reported here, both statistically and economically. For annual earnings forecasts,

Table 2

Forecast Efficiency

	Panel A: Weak Efficiency			Panel B: The Incremental Information Content of Price-Earnings Based Forecasts				
	$\hat{\beta}$	*SE*	$\overline{R}^2$	$\hat{\beta}$	*SE*	$\hat{\gamma}$	*SE*	$\overline{R}^2$
Pooled sample	0.20	(0.08)	0.00	0.05	(0.09)	0.04	(0.01)	0.02
1982	0.73	(0.26)	0.04	0.81	(0.28)	0.03	(0.04)	0.05
1983	0.42	(0.25)	0.01	0.08	(0.27)	0.05	(0.02)	0.04
1984	0.19	(0.27)	0.00	0.03	(0.30)	0.04	(0.02)	0.01
1985	0.05	(0.29)	0.00	0.02	(0.33)	0.01	(0.02)	0.00
1986	0.31	(0.23)	0.01	0.25	(0.22)	0.10	(0.02)	0.06
1987	0.46	(0.22)	0.01	0.41	(0.22)	0.01	(0.02)	0.01
1988	0.42	(0.21)	0.01	0.43	(0.21)	0.00	(0.01)	0.01
1989	0.08	(0.22)	0.00	−0.03	(0.23)	0.03	(0.02)	0.01
1990	0.28	(0.17)	0.01	0.20	(0.20)	0.02	(0.02)	0.01
1991	0.39	(0.17)	0.01	0.11	(0.50)	0.06	(0.03)	0.03
1992	0.09	(0.27)	0.00	−0.20	(0.31)	0.10	(0.03)	0.05

Notes:

Panel A reports the results of the test of the weak efficiency of analysts' forecasts. The regression for the pooled sample is $g_{it} = \alpha_t + \beta g^f_{it} + u_{it}$ where g_{it} is five year earnings growth from January year t to December year t+4 and g^f_{it} is the median forecast of g_{it} reported in April of year t. The regression for the annual samples is $g_{it} = \alpha_t + \beta_t g^f_{it} + u_{it}$. The Panel reports the estimated slope parameter, its Froot-Newey-West adjusted standard error and the adjusted *R*-squared statistic.

Panel B reports the results of the test for the incremental information content of price-earnings based forecasts. The regression for the pooled sample is $g_{it} = \alpha_t + \beta g^f_{it} + \gamma g^p_{it} + u_{it}$ where g_{it} is five year earnings growth from January year t to December year $t+4$, is the median forecast of g_{it} reported in April of year t,

$$g^p_{it} = \frac{p_{it}/pe_{mt} - e_{it}}{e_{it}}, \; pe_{mt} = \frac{1}{N}\sum_{i=1}^{N}\frac{p_{it}}{e_{it}},$$

e_{it} is the earnings reported in December of year $t-1$, and p_{it} is the price in April of year t. The regression for the annual samples is $g_{it} = \alpha_t + \beta_t g^f_{it} + \gamma_t g^p_{it} + u_{it}$. The Panel reports the estimated slope parameter, its Froot-Newey-West adjusted standard error and the adjusted *R*-squared statistic.

Givoly (1985) cannot reject the hypothesis that β is unity. Using UK data on the forecasts of individual analysts, Capstaff et al. (1995) find that the estimated coefficient declines with the forecast horizon, with an estimated value of around 0.5 for 20 month forecasts (their longest horizon). The results of this paper therefore strongly support the view (first offered by DeBondt and Thaler, 1990) that forecast earnings growth is too extreme, and that the longer the horizon, the more extreme it becomes. In the annual regressions, β is significantly less than unity in all years, and significantly greater than zero in only three years. In one year, it is actually significantly negative.

(iv) The Incremental Information Content of Price-Earnings Based Forecasts

The results of regression (5), which supplements analysts' forecasts with forecasts that are derived from the assumption that earnings will evolve in such a way that each firm's price-earnings ratio will converge to the current market price-earnings ratio, are reported in Panel B of Table 2. Under the null hypothesis that analysts make optimal use of information about future earnings that is contained in share prices, the coefficient on the price-earnings based forecast, $\hat{\gamma}$, should be zero. In the pooled sample, the estimated coefficient is significantly greater than zero, implying that analysts do not make full use of information that is readily available at the time that their forecasts are made. However, there is much year to year variation in both the statistical and economic significance of the coefficient, with six years in which the coefficient is not statistically different from zero.

The marginal contribution of price-earnings based forecasts can be gauged by comparing the two Panels of Table 2. The inclusion of the price-earnings forecast explains an additional two percent of the variation in actual earnings growth in the pooled sample, while in individual years, this figure varies between zero and five percent. However, the price-earnings based forecast used in the present analysis is derived under the somewhat unrealistic assumption that all firms have a common long run price-earnings ratio. Undoubtedly, more accurate earnings growth forecasts could be imputed by making more sophisticated assumptions about how price-earnings ratios evolve over time. The results presented here therefore almost certainly understate the extent to which analysts neglect information embodied in share prices. The fact that analysts appear to neglect information contained in share prices when forming their long run earnings growth forecasts is consistent with analogous results for their forecasts over shorter horizons (see, for instance, Ou and Penman, 1989; Abarbanell, 1991; Elgers and Murray, 1992; and Capstaff et al., 1995 and 1998).

(v) Forecast Error Decomposition

The preceding results demonstrate that the accuracy of analysts' long run earnings forecasts is extremely low, and that they are very significantly biased and inefficient. In this sub-section, the source of analysts' forecast error is investigated using the two decompositions of mean square forecast error described in Section 3. The first decomposes forecast error into systematic and non-systematic components. The results of this decomposition are given in Panel A of Table 3. It can be seen that by far the largest component of mean square forecast error is random. In the pooled sample, less than twelve percent of the forecast error is the result of the systematic component of analysts' forecast errors. Of the systematic component, about seven percent is due to bias, and about four percent due to inefficiency. A similar pattern holds for the annual samples, although there is considerable year to year variation, with as much as ninety-five percent of mean square forecast error accounted for by the random component in some years. In principle, knowledge of the systematic error in analysts' forecasts permits the use of 'optimal linear correction' techniques in order to improve forecast accuracy. This involves employing the predicted values calculated using the estimated coefficients from regression (4), above, in place of the forecasts themselves. The effect of the ordinary least squares regression is to adjust the forecasts by compensating for their bias and inefficiency. The degree to which accuracy can be enhanced in this way depends upon the proportion of the mean square forecast error that is systematic. The results reported here imply that, assuming that the underlying data generating process for actual earnings growth and the method by which analysts form the expectations of earnings growth remain constant, optimal linear correction of the forecasts will reduce the forecast error only by about twelve percent. This is clearly an important result for the users of analysts' forecasts.

The second decomposition divides the mean square forecast error into the error in forecasting average earnings growth in the economy, the error in forecasting the deviation of average growth in each industry from average growth in the economy, and the error in forecasting the deviation of earnings growth for

Table 3

Forecast Error Decomposition

	Panel A : Decomposition by Error Type			Panel B: Decomposition by Level of Aggregation		
	Bias	*Inefficiency*	*Random*	*Economy*	*Industry*	*Firm*
Pooled sample	7.51	4.07	88.45	9.21	35.53	55.25
1982	17.67	15.41	67.23	17.67	46.06	36.27
1983	4.37	2.12	93.92	4.37	40.21	55.42
1984	2.38	4.64	93.34	2.38	52.27	45.34
1985	6.07	6.68	87.57	6.07	36.45	57.48
1986	8.00	2.96	89.37	8.00	40.59	51.41
1987	16.73	1.86	81.69	16.73	30.15	53.11
1988	14.10	2.04	84.13	14.10	29.77	56.13
1989	20.02	5.32	74.89	20.02	27.45	52.53
1990	9.62	4.49	86.13	9.62	31.68	58.69
1991	3.35	2.63	94.27	3.35	33.05	63.60
1992	0.26	4.78	95.24	0.26	32.13	67.61

Notes:
Panel A reports the results of the decomposition of mean square forecast error for each year t by error type, given by:

$$\text{MSFE} = \frac{1}{N_t}\sum_{i=1}^{N_t}(g_{it} - g_{it}^f)^2 = (\overline{g}_t - \overline{g}_t^f)^2 + (1-\beta_t)^2\sigma^2_{g^f t} + (1-\rho_t^2)\sigma^2_{gt}$$

where N_t is the sample size in year t, g_{it} is five year earnings growth from January year t to December year t+4, g_{it}^f is the median forecast of g_{it} reported in April of year t, $\overline{g}_t$ and $\overline{g}_t^f$ are the average values of g_{it} and g_{it}^f, β_t is the slope coefficient reported in Panel A of Table 2, ρ_t is the correlation coefficient between g_{it} and g_{it}^f, and σ^2_{gt} and $\sigma^2_{g^f t}$ are the variances of g_{it} and g_{it}^f. The decomposition for the pooled sample is computed over all firms and years.

Panel B reports the results of the decomposition of mean square forecast error for each year t by the level of aggregation, given by:

$$\text{MSFE} = \frac{1}{N_t}\sum_{i=1}^{N_t}(g_{it} - g_{it}^f)^2$$

$$= (\overline{g}_t - \overline{g}_t^f)^2 + \frac{1}{N_t}\sum_{j=1}^{J_t} N_{jt}[(\overline{g}_{jt} - \overline{g}_t) - (\overline{g}_{jt}^f - \overline{g}_t^f)]^2 - \frac{1}{N_t}\sum_{i=1}^{N_t}[(g_{it} - \overline{g}_{jt}) - (g_{it}^f - \overline{g}_{jt}^f)]^2$$

where J_t is the number of industries in the sample, N_{jt} is the number of firms in industry j, $\overline{g}_{jt}$ and $\overline{g}_{jt}^f$ are the average values of g_{it} and g_{it}^f in industry j. The decomposition for the pooled sample is the weighted average of the decompositions for the annual samples, with weights proportional to the sample size each year. The table reports each of the components of mean square forecast error as a percentage of total mean square forecast error.

individual firms from average industry growth. The results of this decomposition are reported in Panel B of Table 3. The results demonstrate that analysts' forecast inaccuracy derives mainly from an inability to forecast deviations of individual firm growth from the average growth rate in its industry. The error in forecasting deviations of industry growth from the average growth rate in the economy is also important, but somewhat smaller than the error in forecasting individual firm growth. In contrast, analysts' inability to forecast average earnings growth in the economy contributes relatively little to their inaccuracy. An interesting feature of this decomposition is that the proportion of forecast error generated at the industry level appears to be diminishing over time, while the proportion generated at the individual firm level is increasing. This is potentially related to changes in the methods used by analysts to forecast earnings growth, or changes in accounting standards.

(vi) The Performance of Analysts' Forecasts Conditional on Firm and Forecast Characteristics

The foregoing analysis has considered analysts' long run earnings growth forecasts as a homogenous group. However, it is likely that forecast performance will vary with the characteristics of the firm whose earnings are being forecast. For instance, one would expect that firms with highly variable cash flows, or those for which little information is available about future earnings prospects, would be associated with lower forecast accuracy. Additionally, forecast performance is likely to vary with the size of the forecast itself since the efficiency results indicate that low forecasts are less overly-optimistic than high forecasts.

In order to investigate this issue, the accuracy, bias and efficiency results are reproduced for sub-samples of companies, partitioned on the basis of market capitalisation, price-earnings ratio, market-to-book ratio and the level of the forecast itself. For each variable, the sample is sorted into ascending order of the partitioning variable and split into quintiles, with equal numbers of firms in each quintile.[10] For all the results of this section, results are reported for quintiles pooled across all years only.

Table 4 presents the results for forecast accuracy, with the mean square forecast error for each quintile reported in Panel A.

There is substantial variation in forecast accuracy across market capitalisation, price-earnings ratio and forecast earnings growth, while there is no obvious systematic variation in forecast accuracy across market-to-book. Forecast accuracy increases with market capitalisation, with forecasts for the quintile of largest firms more than twice as accurate as those for the quintile of smallest firms. There is an inverse relationship between forecast accuracy and price-earnings ratio, with forecasts for the lowest quintile almost three times as accurate as those for the highest quintile. The largest variation in forecast accuracy is with the level of the forecast itself, with low forecasts being five times more accurate than high forecasts. In all three cases, variation in forecast accuracy is monotonic (almost monotonic in the case of price-earnings and forecast size), although it does not appear to be linear, with the largest differences occurring in the lowest and highest quintiles.

The results of Panel A show that forecast accuracy varies substantially with market capitalisation, price-earnings ratio and the forecast itself. However, these variables are not independent, and so variation in forecast accuracy with one variable may merely reflect variation with another. In order to identify the marginal effects of firm and forecast characteristics on forecast accuracy, Panel B of Table 4 reports the regression of the squared forecast error on the natural logarithm of market capitalisation, market-to-book, price-earnings and forecast earnings growth. Interestingly, all four variables independently contribute to the explanation of forecast accuracy, with the most influential, in terms of statistical significance, being the price-earnings ratio, followed by the level of the forecast itself. The most accurate forecasts are therefore low forecasts issued for large companies with low price-earnings ratios and high market-to-book ratios. The four variables together explain more than thirteen percent of the variation in forecast accuracy.

The variation of forecast accuracy with market capitalisation is not surprising. Information about future earnings prospects is likely to be more readily available, and of a higher quality, for larger firms. The variation of forecast accuracy with the forecast itself is consistent with the results on forecast efficiency. The inverse relationship between forecast accuracy and price-earnings ratio is harder to explain, but may be driven by the fact that very

Table 4

Forecast Accuracy Conditional on Firm and Forecast Characteristics

Panel A: Forecast Accuracy by Firm and Forecast Characteristics

	Quintile 1 (lowest)	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5 (highest)*
Capitalisation	11.52	8.24	6.35	5.19	4.47
Market-to-Book	7.84	6.51	6.36	7.18	7.88
Price-Earnings	5.30	4.53	5.02	6.13	14.79
Forecast Size	2.77	6.56	5.70	7.46	13.38

Panel B: The Marginal Effect of Firm and Forecast Characteristics on Forecast Accuracy

	Estimated Coefficient	*Standard Error*
Capitalisation	−103.18	(14.39)
Market-to-Book	17.02	(6.80)
Price-Earnings	24.47	(3.55)
Forecast Growth	42.67	(6.17)
$\overline{R}^2$	0.13	

Notes:

Panel A reports the MSFE in percent for each quintile of firm-year observations sorted in ascending order of market capitalisation, market-to-book ratio, price-earnings ratio and forecast earnings growth.

Panel B reports the estimated slope coefficients from the regression:

$$(g_{it} - g^f_{it})^2 = \alpha_t + \beta_1 \ln m_{it} + \beta_2 mb_{it} + \beta_3 pe_{it} + \beta_4 g^f_{it} + v_{it}$$

where g_{it} is five year earnings growth from January year t to December year $t+4$, g^f_{it} is the median forecast of g_{it} reported in April of year t, m_{it} is the market capitalisation of firm i in April of year t, mb_{it} is the ratio of market capitalisation of firm i in April of year t to the book value of equity firm i in December of year $t-1$ and pe_{it} is the ratio of the share price of firm i in April of year t to the earnings for the fiscal year ending in December of year $t-1$. Froot-Newey-West adjusted standard errors are reported in parentheses. The regression is estimated for the sample pooled over all years.

high price-earnings ratios arise partly as a result of very low, but transitory earnings, the trajectory of which is likely to be difficult to forecast accurately. The positive relationship between forecast accuracy and market-to-book ratio is potentially explained by the fact that high market-to-book companies, *ceteris paribus*, should on average have high earnings growth. Since forecast earnings growth is generally too optimistic, the size of the forecast error for these companies should on average be lower.

Table 5 presents the results for forecast bias. Again, there is strong variation in forecast bias with market capitalisation, price-earnings ratio and the level of the forecast itself. Consistent with the results for forecast accuracy reported in Table 4, forecast bias decreases (in absolute value) with market capitalisation and increases with forecast size. However, while forecast inaccuracy increases with price-earnings ratio, forecast bias *decreases* with price-earnings ratio, implying that while forecasts become less biased as the price-earnings ratio increases, they nevertheless become less accurate. However, this merely implies that the random component of forecast inaccuracy decreases more rapidly with price-earnings ratio than does the systematic component. The largest variation in forecast bias is again with forecast size, with forecasts in the highest quintile being more than four times as biased as those in the lowest quintile. This is consistent with the results on efficiency reported earlier that demonstrate a significant negative relationship between forecast error and the level of the forecast. There is some variation in forecast bias with market-to-book value of equity, although it is not monotonic across quintiles, and the difference between the lowest and highest quintile is not large. There is no quintile of companies for which it can be concluded that analysts' forecasts are unbiased.

Panel B reports the results of the regression of forecast error on market capitalisation, market-to-book value of equity, price earnings ratio and forecast earnings growth. There is again independent variation in forecast bias with market capitalisation, price-earnings ratio and the level of the forecast itself, with the latter being the strongest factor, statistically speaking. There is no significant variation with market-to-book. The four variables together explain about six percent of the variation in forecast error.

These results are broadly consistent with Frankel and Lee (1996), who investigate the performance of analysts' shorter horizon forecasts in order to operationalise an accounting valuation model based on book value of equity and the market's expectation of earnings growth. They find that analyst over-optimism is associated with low book-to-price ratio (the inverse of the market-to-book ratio used in the present analysis) and high past sales growth. They also find that analyst over-optimism is

Table 5

Forecast Bias Conditional on Firm and Forecast Characteristics

Panel A: Forecast Bias by Firm and Forecast Characteristics

	Quintile 1 (lowest)	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5 (highest)*
Capitalisation	−12.28	−8.15	−5.99	−5.34	−5.00
	(0.87)	(0.75)	(0.67)	(0.60)	(0.56)
Market-to-Book	5.32	6.35	8.61	8.08	8.38
	(0.75)	(0.68)	(0.65)	(0.70)	(0.73)
Price-Earnings	−11.66	−6.87	−7.42	−5.48	−5.32
	(0.54)	(0.55)	(0.58)	(0.66)	(1.04)
Forecast Size	3.98	3.56	5.49	7.59	16.12
	(0.44)	(0.69)	(0.64)	(0.71)	(0.90)

Panel B: The Marginal Effect of Firm and Forecast Characteristics on Forecast Bias

	Estimated Coefficient	*Standard Error*
Capitalisation	0.76	(0.28)
Market-to-Book	0.05	(0.05)
Price-Earnings	0.23	(0.05)
Forecast Growth	−0.93	(0.09)
$\bar{R}^2$	0.06	

Notes:

Panel A reports the MFE in percent for each quintile of firm-year observations sorted in ascending order of market capitalisation, market-to-book ratio, price-earnings ratio and forecast earnings growth. Standard errors are reported in parentheses.

Panel B reports the estimated slope coefficients from the regression:

$$(g_{it} - g_{it}^f)^2 = \alpha_t + \beta_1 \ln m_{it} + \beta_2 mb_{it} + \beta_3 pe_{it} + \beta_4 g_{it}^f + \nu_{it}$$

where g_{it} is five year earnings growth from January year t to December year $t+4$, g_{it}^f is the median forecast of g_{it} reported in April of year t, m_{it} is the market capitalisation of firm i in April of year t, mb_{it} is the ratio of market capitalisation of firm i in April of year t to the book value of equity firm i in December of year $t-1$ and pe_{it} is the ratio of the share price of firm i in April of year t to the earnings for the fiscal year ending in December of year $t-1$. Froot-Newey-West adjusted standard errors are reported in parentheses. The regression is estimated for the sample pooled over all years.

associated with forecasts that are high relative to the current level of earnings (i.e. optimistic forecasts). Since forecast earnings growth and actual earnings growth are largely uncorrelated in the present sample, this is consistent with the finding reported above that analyst over-optimism is associated with high forecast earnings growth.

Table 6

Forecast Efficiency Conditional on Firm and Forecast Characteristics

Panel A: Forecast Efficiency by Firm and Forecast Characteristics

	Quintile 1 (lowest)	*Quintile 2*	*Quintile 3*	*Quintile 4*	*Quintile 5 (highest)*
Capitalisation	0.01	0.25	0.12	0.56	1.15
	(0.10)	(0.09)	(0.09)	(0.12)	(0.13)
Market-to-Book	0.05	0.01	0.00	0.08	0.28
	(0.14)	(0.12)	(0.11)	(0.11)	(0.09)
Price-Earnings	−0.31	0.24	0.08	−0.04	−0.21
	(0.09)	(0.10)	(0.11)	(0.12)	(0.11)
Forecast Size	0.84	0.59	0.57	0.60	0.11
	(0.26)	(0.86)	(0.98)	(0.84)	(0.13)

Panel B: The Marginal Effect of Firm and Forecast Characteristics on Forecast Efficiency

	Estimated Coefficient	*Standard Error*
Capitalisation	3.87	(2.30)
Market-to-Book	1.99	(1.14)
Price-Earnings	0.12	(0.63)
Forecast Growth	−12.47	(2.31)
$\overline{R}^2$	0.11	

Notes:

Panel A reports the estimate of β in the regression $g_{it} = \alpha_t + \beta g^f_{it} + u_{it}$ for each quintile of firm-year observations sorted in ascending order of market capitalisation, market-to-book ratio, price-earnings ratio and forecast earnings growth. Froot-Newey-West adjusted standard errors are reported in parentheses.

Panel B reports the estimated slope coefficients from the regression:

$$(g^f_{it} - \overline{g}^f_t)(g_{it} - \overline{g}_t) - (g^f_{it} - \overline{g}^f_t) = \alpha_t + \beta_1 \ln m_{it} + \beta_2 mb_{it} + \beta_3 pe_{it} + \beta_1 g^f_{it} + v_{it}$$

where g_{it} is five year earnings growth from January year t to December year $t+4$. g^f_{it} is the median forecast of g_{it} reported in April of year t, m_{it} is the market capitalisation of firm i in April of year t, mb_{it} is the ratio of market capitalisation of firm i in April of year t to the book value of equity firm i in December of year $t-1$ and pe_{it} is the ratio of the share price of firm i in April of year t to the earnings for the fiscal year ending in December of year $t-1$. Froot-Newey-West adjusted standard errors are reported in parentheses. The regression is estimated for the sample pooled over all years.

Table 6 presents the results for forecast efficiency. Panel A reveals that there is considerable variation in forecast efficiency across both market capitalisation and the level of the forecast, with some variation across market-to-book. The estimated slope parameter, β, is close to zero for the quintile of smallest firms, and rises monotonically with firm size. For the quintile of largest firms, the efficiency condition that $\beta = 1$ cannot be rejected. The estimated slope parameter decreases with the level of forecast, and for the quintile of firms with the lowest forecasts, the null hypothesis that $\beta = 1$ cannot be rejected either. There is no systematic variation with price-earnings ratio. The most efficient forecasts are therefore low forecasts for large firms with high market-to-book ratios.

Panel B of Table 6 reports the marginal contribution of each of the independent variables to forecast efficiency. Consistent with results of Panel A, there is positive independent variation in forecast efficiency with market capitalisation and market-to-book ratio, although the significance is marginal. Also consistent with the quintile results, the relationship between forecast efficiency and forecast growth is very significantly negative. There is no significant variation in forecast efficiency with price-earnings ratio. The four variables together explain eleven percent of the variation in forecast efficiency.

5. SUMMARY AND CONCLUSIONS

This paper has undertaken a detailed study of the accuracy, bias and efficiency of analysts' forecasts of long run earnings growth for US companies. The results of the paper can be summarised as follows.

(i) The accuracy of analysts' long run earnings growth forecasts is extremely low. Superior forecasts can be achieved simply by assuming that long run earnings growth is zero.

(ii) Analysts' forecasts are excessively optimistic. Forecast earnings growth, on average, exceeds actual earnings growth by about seven percent per annum.

(iii) Analysts' forecasts are weakly inefficient. Forecast errors are not independent of the forecasts themselves. In particular, high forecasts are associated with high forecast errors, while low forecasts are associated with low forecast errors.

(iv) Analysts' forecasts do not incorporate all information contained in current share prices. A superior forecast can be obtained by assuming that each firm's earnings will evolve in such a way that its price-earnings ratio will converge to the current market-wide price-earnings ratio.

(v) Despite the bias and inefficiency identified in (ii) and (iii) above, the systematic components of analysts' forecast errors contribute relatively little to their inaccuracy. More than eighty-eight percent of the mean square forecast error is random. This is an important result for the users of analysts' long run earnings growth forecasts, since it means that the accuracy of analysts' forecasts cannot be significantly improved using linear correction techniques.

(vi) The largest part of analysts' forecast error is made at the individual firm level. The inability of analysts to forecast average earnings growth in the economy does not contribute substantially to their inaccuracy. However, there is evidence that the level of aggregation at which analysts' errors are being made is changing over time, with increasing accuracy at the industry level, and decreasing accuracy at the individual firm level.

(vii) There is significant heterogeneity in the performance of analysts' forecasts. The most reliable earnings growth forecasts are low forecasts issued for large companies with low price-earnings and high market-to-book ratios. The least biased forecasts are those for low forecasts for companies with low price-earnings ratios, while the most efficient forecasts are low forecasts for large companies with high market-to-book ratios. This is again an important result for the users of analysts' forecasts since it offers some opportunity to discriminate between good and bad forecasts.

(viii) There is very little evidence to suggest that the inaccuracy, bias or inefficiency of analyst' forecasts have diminished over time.

The idea that analysts systematically make over-optimistic forecasts, is not necessarily an indictment of their rationality *per se* since they may have considerable incentives to do so. An earnings growth forecast is not generally the final product delivered by an analyst to the client. In particular, earnings growth forecasts will be typically provided as part of a package of services, including brokerage, advice on mergers and acquisitions, and underwriting, and these related activities may influence the forecasts that an analyst makes (see Schipper, 1991). Sell-side analysts, for instance, have a vested interest in their clients' reaction to earnings forecasts. If earnings forecasts are used to support stock recommendations then high forecasts will tend to generate more business than low forecasts, since there is a larger potential client base for buy recommendations than for sell recommendations. Francis and Philbrick (1993) provide evidence that suggests that analysts may be intentionally over-optimistic in order to cultivate and maintain good management relations.

The decomposition of mean square forecast error by error type revealed that by far the largest component of analysts' forecast errors is random, with the systematic component accounting for less than twelve percent. Inevitably, at such long forecasting horizons, the potential to make accurate forecasts of earnings growth is limited. However, the fact that such a large component of actual earnings growth is random may explain why analysts' forecasts are so biased. The larger the component of the forecast error that is random, the lower the impact of forecast bias on forecast error. Assuming that analysts do have conflicting objectives — one to produce *accurate* earnings growth forecasts, the other to produce *high* earnings growth forecasts — then if analysts know that the first objective is largely unattainable, they will use the forecasting process to satisfy the second. If analysts are also producing short term and interim forecasts for the same company, then the bias in their long term forecasts may be compounded.

A number of papers have now concluded that there is substantial mis-pricing in the stock market as a consequence of irrational long run earnings growth forecasts being incorporated into the market expectation of earnings growth. The results of this paper support the hypothesis that analysts' consensus long run earnings growth forecasts are indeed irrational if they are to be interpreted as optimal forecasts of future earnings growth. However, given the uncertainty over analysts' incentives, it is by no means inevitable that these forecasts will be incorporated without modification into the market expectation of earnings growth. An interesting topic for future research will be to examine to what extent the market recognises the characteristics in forecast long run earnings growth identified in this paper.

NOTES

1 A partial list would include Brown and Rozeff (1978), Brown et al. (1987a and 1987b) and O'Brien (1988) who consider the performance of analysts' quarterly earnings forecasts, and Collins and Hopwood (1980), Fried and Givoly (1982) and Brown et al. (1985), who consider analysts' annual forecasts. International evidence on analysts' forecasts is provided by Capstaff et al. (1995), who analyse the performance of UK analysts, and Capstaff et al. (1998), who consider the forecasts of European analysts. For a comprehensive survey of the literature on analysts' earnings forecasts, see Brown (1993).

2 This was confirmed in conversation with IBES staff.

3 The correlation between the mean and the median forecast in the sample is 0.98. This is accounted for by the fact that most stocks have long term forecasts originating from only one or two analysts.

4 IBES have confirmed that they do receive earnings growth forecasts for companies whose earnings are currently negative. This may be explained by the fact that while analysts use the latest reported earnings as a base for earnings growth when earnings are positive, they use some other unspecified base measure of earnings, such as forecast annual earnings or average historical annual earnings, when earnings are negative.

5 In order to establish the robustness of the results, the analysis was conducted using maximum earnings growth threshold values in the range 50% to 1,000%, and by trimming the sample instead on the basis of initial earnings per share, using a minimum earnings threshold of between 0.10 and 1.00 dollars. The sensitivity of the results to changes in the threshold values was low, and none of the qualitative conclusions were altered. The regressions were additionally estimated using the minimum absolute deviation estimator, which is considerably less sensitive to outliers. This produced results that were almost completely invariant with respect to the choice threshold values. As a further test of the robustness of the results, the analysis was conducted using the change in earnings scaled by price, with the corresponding forecast change in earnings computed using the forecast growth rate. The results of these robustness tests are not reported here, but are available from the author on request.

6 The average growth rate is taken over all firms for which earnings data are available, using the same sample selection criteria as for subsequent earnings growth, namely excluding observations for which earnings are negative at the beginning of the five year period, and those for which the calculated growth rate exceeds 100% in absolute value.

7 This can be seen by subtracting forecast earnings growth, g^f_{it}, from each side so that the regression becomes one of forecast error on forecast earnings growth — the constant remains the same while the slope parameter becomes $\beta - 1$.

8 Taking the conditional expectation of equations (10) and (11) gives the mean square forecast error and the mean forecast error, respectively, as a function of the independent variables. Regressions (10) and (11) thus measure the marginal contribution of each of the independent variables to forecast accuracy and forecast bias. Taking the conditional expectation of equation (12) gives the covariance between $(g_{it} - g^f_{it})$ and g^f_{it} as a function of the independent variables. This covariance is the numerator of the estimated slope coefficient in a regression of $g_{it} - g^f_{it}$ on g^f_{it}. Under the

null hypothesis that forecasts are weakly efficient, this covariance should be equal to zero. If it is less than zero, forecasts are too extreme, while if it is greater than zero, forecasts are too compressed. Regression (12) thus measures the marginal contribution of each of the independent variables to forecast efficiency.

9 See, for example, Brown et al. (1987a) and O'Brien (1988), who consider the accuracy of analysts' quarterly earnings forecasts relative to the forecasts of different time series models, and Fried and Givoly (1982), who consider the relative accuracy of analysts' annual earnings forecasts.

10 Except for the largest quintile, which has an additional observation.

REFERENCES

Abarbanell, J. (1991), 'Do Analysts' Earnings Forecasts Incorporate Information in Prior Stock Price Changes?' *Journal of Accounting and Economics*, Vol. 14, pp. 147–66.

Alford, A., J. Jones and M. Zmijewski (1994), 'Extensions and Violations of the Statutory SEC Form 10-K Filing Requirements', *Journal of Accounting and Economics*, Vol. 17, pp. 229–54.

Brooks, L. and D. Buckmaster (1976), 'Further Evidence on the Time Series Properties of Accounting Income', *Journal of Finance*, Vol. 31, pp. 1359–73.

Brown, L. (1993), 'Earnings Forecasting Research: Its Implications for Capital Markets Research', *International Journal of Forecasting*, Vol. 9, pp. 295–320.

________ (1997), 'Analyst Forecasting Errors: Additional Evidence', Working Paper (University at Buffalo).

________ and M. Rozeff (1978), 'The Superiority of Analysts' Forecasts as Measures of Expectations: Evidence from Earnings', *Journal of Finance*, Vol. 33, pp. 1–16.

________ R. Hagerman, P. Griffin and M. Zmijewski (1987a), 'Security Analyst Superiority Relative to Univariate Time-Series Models in Forecasting Quarterly Earnings', *Journal of Accounting and Economics*, Vol. 9, pp. 61–87.

________ ________ ________ ________ (1987b), 'An Evaluation of Alternative Proxies for the Market's Assessment of Unexpected Earnings', *Journal of Accounting and Economics*, Vol. 9, pp. 159–93.

Brown, P., G. Foster and E. Noreen (1985), 'Security Analyst Multi-Year Earnings Forecasts and the Capital Market', *American Accounting Association Studies in Accounting Research*, Vol. 21.

Bulkley, G. and R. Harris (1997), 'Irrational Analysts' Expectations as a Cause of Excess Volatility in Stock Prices', *Economic Journal*, Vol. 107, pp. 359–71.

Capstaff, J., K. Paudyal and W. Rees (1995), 'The Accuracy and Rationality of Earnings Forecasts by UK Analysts', *Journal of Business, Finance & Accounting*, Vol. 22, pp. 67–85.

________ ________ ________ (1998), 'A Comparative Analysis of Earnings Forecasting in Europe', manuscript (University of Glasgow).

Christie, A. (1987), 'On Cross-Sectional Analysis in Accounting Research', *Journal of Accounting and Economics*, Vol. 9, pp. 231–58.

Collins, W. and W. Hopwood (1980), 'A Multivariate Analysis of Annual Earnings Forecasts Generated from Quarterly Forecasts of Financial Analysts and Univariate Time-Series Models', *Journal of Accounting Research* Vol. 18, pp. 390–406.

DeBondt, W. (1992), *Earnings Forecasts and Share Price Reversals* (Foundation of Chartered Financial Analysts, Charlottsville, Virginia).

________ and R. Thaler (1990), 'Do Security Analysts Overreact?' *American Economic Review*, Vol. 80, pp. 52–57.

Dechow, P. and R. Sloan (1997), 'Returns to Contrarian Investment Strategies: Tests of Naive Expectations Hypotheses', *Journal of Financial Economics*, Vol. 43, pp. 3–27.

Elgers, P., and D. Murray (1992), 'The Relative and Complementary Performance of Analyst and Security-Price Based Measures of Expected Earnings', *Journal of Accounting and Economics*, Vol. 15, No. 303–16.

Elton, E., M. Gruber and M. Gultekin (1984), 'Professional Expectations: Accuracy and Diagnosis of Errors', *Journal of Financial and Quantitative Analysis*, Vol. 19, pp. 351–62.

Foster, G. (1977), 'Quarterly Accounting Data: Time Series Properties and Predictive-Ability Results', *Accounting Review*, Vol. 52, pp. 1–21.

Francis, J. and D. Philbrick (1993), 'Analysts' Decisions as Products of a Multi-Task Environment', *Journal of Accounting Research*, Vol. 31, pp. 216–30.

Frankel, R. and C. Lee (1996), 'Accounting Valuation, Market Expectation, and the Book-to-Market Effect', *Journal of Finance*, Vol. 51, pp. 1040–41.

Fried, D. and D. Givoly (1982), 'Financial Analysts' Forecasts of Earnings', *Journal of Accounting and Economics*, Vol. 4, pp. 85–107.

Froot, K. (1989), 'Consistent Covariance Matrix Estimation with Cross-Sectional Dependence and Heteroskedasticity in Financial Data', *Journal of Financial and Quantitative Analysis*, Vol. 24, pp. 333–55.

Givoly, D. (1985), 'The Formation of Earnings Expectations', *Accounting Review*, Vol. 60, pp. 372–86.

Lakonishok, J., A. Schleifer and R. Vishny, (1994), 'Contrarian Investment, Extrapolation, and Risk', *Journal of Finance*, Vol. 49, pp. 1541–78.

La Porta, R. (1996), 'Expectations and the Cross-Section of Stock Returns', *Journal of Finance*, Vol. 51, pp. 1715–42.

Mincer, J. and V. Zarnovitz (1969), 'The Valuation of Economic Forecasts', in J. Mincer (ed.), *Economic Forecasts and Expectations* (National Bureau of Economic Research).

Newey, W. and K. West (1987), 'A Simple Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix', *Econometrica*, Vol. 55, pp. 703–8.

O'Brien, P. (1988), 'Analysts' Forecasts as Earnings Expectations', *Journal of Accounting and Economics*, Vol. 10, pp. 53–83.

Ou, J. and S. Penman (1987), 'Financial Statement Analysis and the Prediction of Stock Returns', *Journal of Accounting and Economics*, Vol. 11, pp. 295–330.

Ramakrishnan, R. and J. Thomas (1992), 'What Matters from the Past: Market Value, Book Value or Earnings? Earnings Valuation and Sufficient Statistics for Prior Information', *Journal of Accounting, Auditing and Finance*, Vol. 7, pp. 423–64.

Schipper, K. (1991), 'Commentary on Analysts' Forecasts', *Accounting Horizons*, Vol. 5, pp. 105–21.

Theil, H. (1961), *Optimal Decision Rules for Government and Industry* (North Holland).

________ (1966), *Applied Economic Forecasting* (North Holland).

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THE MARKET RISK PREMIUM:
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The Market Risk Premium: Expectational Estimates Using Analysts' Forecasts

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The Market Risk Premium: Expectational Estimates Using Analysts' Forecasts

Abstract

We use expectational data from financial analysts to estimate a market risk premium for U.S. stocks. Using the SP500 as a proxy for the market portfolio, we find an average market risk premium of 7.14% above yields on long-term U.S. government bonds over the period 1982-1998. We also find that this risk premium varies over time and that much of this variation can be explained by either the level of interest rates or readily available forward-looking proxies for risk. The market risk premium appears to move inversely with government interest rates suggesting that required returns on stocks are more stable than interest rates themselves.

The Market Risk Premium: Expectational Estimates Using Analysts' Forecasts

The notion of a market risk premium (the spread between investor required returns on safe and average risk assets) has long played a central role in finance. It is a key factor in asset allocation decisions to determine the portfolio mix of debt and equity instruments. Moreover, the market risk premium plays a critical role in the Capital Asset Pricing Model (CAPM), practitioners most widely used means of estimating equity hurdle rates. In recent years, the practical significance of estimating such a market premium has increased as firms, financial analysts and investors employ financial frameworks to analyze corporate and investment performance. For instance, the increased use of Economic Value Added to assess corporate performance has provided a new impetus for estimating capital costs.

The most prevalent approach to estimating the market risk premium relies on some average of the historical spread between returns on stocks and bonds.[1] This choice has some appealing characteristics but is subject to many arbitrary assumptions such as the relevant period for taking an average. Compounding the difficulty of using historical returns is the well noted fact that standard models of consumer choice would predict much lower spreads between equity and debt returns than have occurred in U.S. markets—the so called equity premium puzzle (see Welch (1998), Siegel and Thaler (1997)). In addition, theory calls for a forward looking risk premium that could well change over time.

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[1] Bruner, Eades, Harris and Higgins (1998) provide survey evidence on both textbook advice and practitioner methods for estimating capital costs. Despite substantial empirical assault, the CAPM continues to play a major role in applied finance. As testament to the market for cost of capital estimates Ibbotson Associates (1998) publishes a "Cost of Capital Quarterly."

This paper takes an alternate approach by using expectational data to estimate the market risk premium. The approach has two major advantages for practitioners. First, it provides an independent estimate which can be compared to historical averages. At a minimum, this can help in understanding likely ranges for risk premia. Second, expectational data allow investigation of changes in risk premia over time. Such time variations in risk premia serve as important signals from investors that should affect a host of financial decisions.

The paper updates and extends earlier work (Harris (1986), Harris and Marston (1992)) which incorporates financial analysts' forecasts of corporate earnings growth. Updating through 1998 provides an opportunity to see whether changes in the risk premium are in part responsible for the run up in share prices in the bull market. In addition, we provide new tests of whether changes in risk premia over time are linked to forward-looking measures of risk. Specifically, we look at the relationship between the risk premium and four ex-ante measures of risk: the spread between yields on corporate and government bonds, consumer sentiment about future economic conditions, the average level of dispersion across analysts as they forecast corporate earnings and the implied volatility on the SP500 Index derived from options data.

Section I provides background on the estimation of equity required returns and a brief discussion of current practice in estimating the market risk premium. In Section II, models and data are discussed. Following a comparison of the results to historical returns in Section III, we examine the time-series characteristics of the estimated market premium in Section IV. Finally, conclusions are offered in Section V.

I. Background

The notion of a "market" required rate of return is a convenient and widely used construct. Such a rate (k) is the minimum level of expected return necessary to compensate investors for bearing the average risk of equity investments and receiving dollars in the future rather than in the present. In general, k will depend on returns available on alternative investments (e.g., bonds). To isolate the effects of risk, it is useful to work in terms of a market risk premium (*rp*), defined as

$$rp = k - i, \tag{1}$$

where i = required return for a zero risk investment.

Lacking a superior alternative, investigators often use averages of historical realizations to estimate a market risk premium. Bruner *et al.* (1998) provide recent survey results on best practices by corporations and financial advisors. While almost all respondents used some average of past data in estimating a market risk premium, a wide range of approaches emerged. "While most of our 27 sample companies appear to use a 60+- year historical period to estimate returns, one cited a window of less than ten years, two cited windows of about ten years, one began averaging with 1960, and another with 1952 data" (p. 22). Some used arithmetic averages and some geometric. This historical approach requires the assumptions that past realizations are a good surrogate for future expectations and, as typically applied, that the risk premium is constant over time. Carleton and Lakonishok (1985) demonstrate empirically some of the problems with such historical premia when they are dissaggregated for different time periods or groups of firms. As Bruner *et al* (1998) point out, few respondents cited use of expectational data to supplement or replace historical returns in estimating the market premium.

Survey evidence also shows substantial variation in empirical estimates. When respondents gave a precise estimate of the market premium, they cited figures from 4 to over 7 percent (Bruner *et al* 1998). A quote from a survey respondent highlights the range in practice. "In 1993, we polled various investment banks and academic studies on the issue as to the appropriate rate and got anywhere between 2 and 8%, but most were between 6 and 7.4%." (Bruner *et al* 1998, p. 23). An informal sampling of current practice also reveals large differences in assumptions about an appropriate market premium. For instance, in a 1999 application of EVA analysis, Goldman Sachs Investment Research specifies a market risk premium of "3%

from 1994-1997 and 3.5% from 1998-1999E for the S&P Industrials" (Goldman Sachs (1999, p. 59)). At the same time an April 1999 phone call to Stern Stewart revealed that their own application of EVA typically employed a market risk premium of 6%. In its application of the CAPM, Ibbotson Associates (1998) uses a market risk premium of 7.8%. Not surprisingly, academics don't agree on risk premium either. Welch (1998) surveyed leading financial economists at major universities. For a 30-year horizon, he found a mean risk premium of 6.12% but a range from 2% to 9% with an interquartile range of 2% (based on 104 responses).

To provide additional insight on estimates of the market premium, we use publicly available expectational data. This expectational approach employs the dividend growth model (hereafter referred to as the discounted cash flow or DCF model) in which a consensus measure of financial analysts' forecasts (FAF) of earnings is used as a proxy for investor expectations. Earlier works by Malkiel (1982), Brigham, Vinson, and Shome (1985), Harris (1986) and Harris and Marston (1992) have used FAF in DCF models[2].

II. Models and Data

We employ the simplest and most commonly used version of the DCF model to estimate shareholders' required rate of return, k, as shown in Equation (2):

$$k = \left(\frac{D_1}{P_0}\right) + g, \tag{2}$$

where D_1 = dividend per share expected to be received at time one, P_0 = current price per share (time 0), and g = expected growth rate in dividends per share[3]. A primary difficulty in using the

[2] Ibbotson Associates (1998) use a variant of the DCF model with forward-looking growth rates as one means to estimate cost of equity; however, they do this as a separate technique and not as part of the CAPM. For their CAPM estimates they use historical averages for the market risk premium. The DCF approach with analysts' forecasts has been used frequently in regulatory settings.

[3] Our methods follow Harris (1986) and Harris and Marston (1992) who provide an overview of earlier research and a detailed discussion of the approach employed here. For instance, theoretically, i is a risk-free rate, though empirically its proxy (e.g., yield to maturity on a government bond) is only a "least risk" alternative that is itself subject to risk. They also discuss single versus multistage growth discounted cash flow models and procedures used in calculating the expected dividend yield. While the model calls for expected growth in dividends, in the long run, dividend growth is sustainable only via growth in earnings. As long as payout ratios are not expected to change, the two growth rates will be the same.

DCF model is obtaining an estimate of g, since it should reflect market expectations of future performance. This paper uses published FAF of long-run growth in earnings as a proxy for g. Equation (2) can be applied for an individual stock or any portfolio of companies. We focus primarily on its application to estimate a market premium as proxied by the SP500.

FAF come from IBES Inc. The mean value of individual analysts' forecasts of five-year growth rate in EPS is used as our estimate of g in the DCF model. The five-year horizon is the longest horizon over which such forecasts are available from IBES and often is the longest horizon used by analysts. IBES requests "normalized" five-year growth rates from analysts in order to remove short-term distortions that might stem from using an unusually high or low earnings year as a base. Growth rates are available on a monthly basis.

Dividend and other firm-specific information come from COMPUSTAT. D_1 is estimated as the current indicated annual dividend times (1+g). Interest rates (both government and corporate) are gathered from Federal Reserve Bulletins and *Moody's Bond Record*. Table 1 describes key variables used in the study. Data are collected for all stocks in the Standard & Poor's 500 stock (SP500) index followed by IBES. Since five-year growth rates are first available from IBES beginning in 1982, the analysis covers the period from January 1982-December 1998.

We generally adopt the same approach as used in Harris and Marston (1992). For each month, a market required rate of return is calculated using each dividend paying stock in the SP500 index for which data are available. As additional screens for reliability of data, in a given month we eliminate a firm if there are fewer than three analysts' forecasts or if the standard deviation around the mean forecast exceeds 20%. Combined these two screens eliminate fewer than 20 stocks a month. Later we report on the sensitivity of our results to various screens. The DCF model in Equation (2) is applied to each stock and the results weighted by market value of equity to produce the market-required return.[4] The risk premium is constructed by subtracting the interest rate on government bonds.

For short-term horizons (quarterly and annual), past research (Brown, 1993) finds that on average analysts' forecasts are overly optimistic compared to realizations. However, recent research on quarterly horizons (Brown, 1997) suggests that analysts' forecasts for SP500 firms do not have an optimistic bias for the period 1993-1996. There is very little research on the properties of five-year growth forecasts, as opposed to shorter horizon predictions.[5] Any analysts' optimism is not necessarily a problem for our analysis. If investors share analysts' views, our procedures will still yield unbiased estimates of required returns and risk premia. In light of the possible bias, however, we interpret our estimates as "upper bounds" for the market premium.

To broaden our exploration, we tap four very different sources to create ex ante measures of equity risk at the market level. The first proxy comes from the bond market and is calculated as the spread between corporate and government bond yields (BSPREAD). The rationale is that increases in this spread signal investors' perceptions of increased riskiness of corporate activity that would be translated to both debt and equity owners. The second measure, CON, is the consumer confidence index reported by the Conference Board at the end of the month. While the reported index tends to be around 100, we rescale CON as the actual index divided by 100. We also examined use of CON as of the end of the prior month; however, in regression analysis

[4] We weighted 1998 results by year-end 1997 market values since our monthly data on market value did not extend through this period. Since we did not have data on firm-specific dividend yields for the last four months of 1998, we estimated the market dividend yield for these months using the dividend yield reported in the *Wall Street Journal* scaled by the average ratio of this figure to the dividend yield for our sample as calculated in the first eight months of 1998. We then made adjustments using growth rates from IBES to calculate the market required return. We also estimated results using an average dividend yield for the month which employed the average of the price at the end of the current and prior months. These average dividend yield measures led to essentially the same regression coefficients as those reported later in the paper but introduced significant serial correlation in some regressions (Durbin-Watson statistics significantly different from 2.0 at the .01 level).

[5] To our knowledge, the only studies of possible bias in analysts' five-year growth rates are Boebel (1991) and Boebel, Harris and Gultekin (1993). They both find evidence of optimism in IBES growth forecasts. In the most thorough study to date, Boebel (1991) reports that this bias seems to be getting smaller over time. His forecast data do not extend into the 1990's.

this lagged measure was generally not statistically significant in explaining the level of the market risk premium[6]. The third measure, DISP, measures the dispersion of analysts' forecasts. Such analyst disagreement should be positively related to perceived risk since higher levels of uncertainty would likely generate a wider distribution of earnings forecasts for a given firm. DISP is calculated as the equally weighted average of firm-specific standard deviations for each stock in the SP500 covered by IBES. The firm-specific standard deviation is calculated based on the dispersion of individual analysts' growth forecasts around the mean of individual forecasts for that company in that month. Our final measure, VOL, is the implied volatility on the SP500 index. As of the beginning of the month, we use a dividend adjusted Black Scholes Formula to estimate the implied volatility in the SP500 index option contract which expires on the third Friday of the month. The call premium, exercise price and the level of the SP500 index are taken from the *Wall Street Journal* and treasury yields come from the Federal Reserve. Dividend yield comes from DRI. We use the option contract that is closest to being at the money.

III. Estimates of the Market Premium

Table 2 reports both required returns and risk premia by year (averages of monthly data). The results are quite consistent with the patterns reported earlier (e.g., Harris and Marston, 1992). The estimated risk premia are positive, consistent with equity owners demanding additional rewards over and above returns on debt securities. The average expectational risk premium (1982 to 1998) over government bonds is 7.14%, slightly higher than the 6.47% average for 1982 to 1991 reported earlier (Harris and Marston, 1992). For comparison purposes, Table 3 contains historical returns and risk premia. The average expectational risk premium

[6] We examined two other proxies for Consumer Confidence. The Conference Board's Consumer Expectations Index yielded essentially the same results as those reported. The University of Michigan's Consumer Sentiment Indices tended to be less significantly linked to the market risk premium though coefficients were still negative.

reported in Table 2 is approximately equal to the arithmetic (7.5%) long-term differential between returns on stocks and long-term government bonds.[7]

Table 2 shows the estimated risk premium changes over time, suggesting changes in the market's perception of the incremental risk of investing in equity rather than debt securities. Scanning the next to last column of Table 2, the risk premium is higher in the 1990's than earlier and especially so in late 1997 and 1998. Our DCF results provide no evidence to support the notion of a declining risk premium in the 1990's as a driver of the strong run up in equity prices.

A striking feature in Table 2 is the relative stability of our estimates of k. After dropping (along with interest rates) in the early and mid-1980's, the average annual value of k has remained within a 75 basis point range around 15 percent for over a decade. Moreover, this stability arises despite some variability in the underlying dividend yield and growth components of k as Table 2 illustrates. The results suggest that k is more stable than government interest rates. Such relative stability of k translates into parallel changes in the market risk premium. In a subsequent section, we examine whether changes in our market risk premium estimates appear linked to interest rate conditions and a number of proxies for risk[8].

We explored the sensitivity of our results to our screening procedures in selecting companies. Our reported results screen out all non-dividend paying stocks on the premise that use of the DCF model is inappropriate in such cases. The dividend screen eliminates an average of 55 companies per month. In a given month, we also screen out firms with fewer than three analysts' forecasts, or if the standard deviation around the mean forecast exceeds 20%. When we repeated our analysis without any of the screens, the average risk premium over the sample

[7] Interestingly, for the 1982-1996 period the arithmetic spread between large company stocks and long-term government bonds was only 3.3% per year. The downward trend in interest rates resulted in average annual returns of 14.1% on long-term government bonds over this horizon. Some (e.g., Ibbotson, 1997) argue that only the income (not total) return on bonds should be subtracted in calculating risk premia.

[8] Although our focus is on the market risk premium, in earlier work (Harris and Marston (1992), Marston, Harris and Crawford (1993)), we examined the cross-sectional link between expectational equity risk premia at the firm level and beta and found a significant positive correlation. For comparative purposes, we replicated and updated that

period increased by only 40 basis points, from 7.14% to 7.54%. We also estimated the beta of our sample firms and found the sample average to be one, suggesting that our screens do not systematically remove low or high-risk firms. Specifically, using firms in our screened sample as of December 1997 (the last date for which we had CRSP return data), we used ordinary least squares regressions to estimate beta for each stock using the prior sixty months of data and the CRSP return (SPRTRN) as the market index. The value-weighted average of the individual betas was 1.00.

In the results reported here we use firms in the SP500 as reported by COMPUSTAT in September 1998 which could create a survivorship bias, especially in the earlier months of our sample. We compared our current results to those obtained in our earlier work (Harris and Marston (1992)) for which we had data to update the SP500 composition each month. For the overlapping period, January 1982-May 1991 the two procedures yield the same average market risk premium, 6.47%. This suggests that the firms departing from or entering the SP500 index do so for a number of reasons with no discernable effect on the overall estimated SP500 market risk premium.

IV. Changes in the Market Risk Premium Over Time

With changes in the economy and financial markets, equity investments may be perceived to change in risk. For instance, investor sentiment about future business conditions likely affects attitudes about the riskiness of equity investments compared to investments in the bond markets. Moreover, since bonds are risky investments themselves, equity risk premia (relative to bonds) could change due to changes in perceived riskiness of bonds, even if equities displayed no shifts in risk.

In earlier work covering the 1982-1991 period, Harris and Marston (1992) reported regression results indicating that the market premium decreased with the level of government

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analysis through 1998 and reached very similar conclusions. At the firm level our expectational estimates of risk interest rates and increased with the spread between corporate and government bond yields (BSPREAD). This bond yield spread was interpreted as a time series proxy for equity risk. We introduce three additional ex ante measures of risk shown in Table 1: CON, DISP and VOL. The three measures come from three independent sets of data and are supplied by different agents in the economy (consumers, equity analysts and investors (via option and share price data)). Table 4 provides summary data on all four of our risk measures.

Table 5 replicates and updates earlier analysis.[9] The results confirm the earlier patterns. For the entire sample period, Panel A shows that risk premia are negatively related to interest rates. This negative relationship is also true for both the 1980's and 1990's as displayed in Panels B and C. For the entire 1982 to 1998 period, the addition of the yield spread risk proxy to the regressions lowers the magnitude of the coefficient on government bond yields, as can be seen by comparing Equations 1 and 2 of Panel A. Furthermore, the coefficient of the yield spread (0.487) is itself significantly positive. This pattern suggests that a reduction in the risk differential between investment in government bonds and in corporate activity is translated into a lower equity market risk premium.

In major respects, the results in Table 5 parallel earlier findings. The market risk premium changes over time and appears inversely related to government interest rates but positively related to the bond yield spread, which proxies for the incremental risk of investing in equities as opposed to government bonds. One striking feature is the large negative coefficients on government bond yields. The coefficients indicate the equity risk premium declines by over 70 basis points for a 100 basis point increase in government interest rates.[10] This inverse

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premia are significantly positively correlated to beta.

[9] OLS regressions with levels of variables generally showed severe autocorrelation. As a result, we used the Prais-Winsten method (on levels of variables) and also OLS regressions on first differences of variables. Since both methods yielded similar results and the latter had more stable coefficients across specifications, we report only the results using first differences. Tests using Durbin-Watson statistics from regressions in Tables 5 and 6 do not accept the hypothesis of autocorrelated errors (tests at .01 significance level, see Johnston 1984, pp. 321-325).

[10] The Table 5 coefficients on i are significantly different from –1. 0 suggesting that equity required returns do respond to interest rate changes. However, the large negative coefficients imply only minor adjustments of required

relationship suggests much greater stability in equity required returns than is often assumed. For instance, standard application of the CAPM suggests a one-to-one change in equity returns and government bond yields.

Table 6 introduces three additional proxies for risk and explores whether these variables, either individually or collectively, are correlated with the market premium. Since our estimates of implied volatility start in May 1986, the table shows results for both the entire sample period and for the period during which we can introduce all variables. Entered individually each of the three variables is significantly linked to the risk premium with the coefficient having the expected sign. For instance, in regression (1) the coefficient on CON is -.014 which is significantly different from zero (t = -3.50). The negative coefficient signals that higher consumer confidence is linked to a lower market premium. The positive coefficients on VOL and DISP indicate the equity risk premium increases with both market volatility and disagreement among analysts. The effects of the three variables appear largely unaffected by adding other variables. For instance, in regression (4) the coefficients on CON and DISP both remain significant and are similar in magnitude to the coefficients in single variable regressions.

Even in the presence of the new risk variables, Table 6 shows that the market risk premium is affected by interest rate conditions. The large negative coefficient on government bond rates implies large reductions in the equity premium as interest rates rise. One feature of our data may contribute to the observed negative relationship between the market risk premium and the level of interest rates. Specifically, if analysts are slow to report updates in their growth forecasts, changes in our estimated *k* would not adjust fully with changes in the interest rate even if the true risk premium were constant. To address the impact of "stickiness" in the measurement of *k*, we formed "quarterly" measures of the risk premium which treat *k* as an average over the

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returns to interest rate changes since the risk premium declines. In earlier work (Harris and Marston (1991)) the coefficient was significantly negative but not as large in absolute value. In that earlier work we reported results quarter. Specifically, we take the value of k at the end of a quarter and subtract from it the average value of i for the months ending when k is measured. For instance, to form the risk premium for March 1998 we take the March value of k and subtract the average value of i for January, February and March. This approach assumes that in March k still reflects values of g that have not been updated from the prior two months. We then pair our quarterly measure of risk premium with the average values of the other variables for the quarter. For instance, the March 1998 "quarterly" risk premium would be paired with averaged values of BSPREAD over the January through March period. To avoid overlapping observations for the independent variables, we use only every third month (March, June, September, December) in the sample.

As reported in Table 7, sensitivity analysis using "quarterly" observations suggests that delays in updating may be responsible for a portion, but not all, of the observed negative relationship between the market premium and interest rates. For example, when we use quarterly observations the coefficient on i in regression (2) of Table 7 is -.527, well below the earlier estimates but still significantly negative[11].

As an additional test, we look at movements in the bond risk premium (BSPREAD). Since BSPREAD is constructed directly from bond yield data it does not have the potential for reporting lags that may affect analysts' growth forecasts. Regression 3 in Table 7 shows BSPREAD is negatively linked to government rates and significantly so[12]. While the equity premium need not move in the same pattern as the corporate bond premium, the negative coefficient on BSPREAD suggests that our earlier results are not due solely to "stickiness" in measurements of market required returns.

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using the Prais-Winsten estimators. When we use that estimation technique and recreate the second regression in Table 5, the coefficient for i is -.584 (t = 12.23) for the entire sample period 1982-1998.

[11] Sensitivity analysis for the 1982-1989 and 1990-1998 subperiods yields results similar to those reported.

[12] We thank Bob Conroy for suggesting use of BSPREAD. Regression 3 in Table 7 appears to have autocorrelated errors: the Durbin-Watson (DW) statistic rejects the hypothesis of no autocorrelation. However, in subperiod analysis, the DW statistic for the 1990-98 period is consistent with no autocorrelation and the coefficient on i is essentially the same (-.24, t = -8.05) as reported in Table 7.

The results in Table 7 suggest that the inverse relationship between interest rates and the market risk premium may not be as pronounced as suggested in earlier tables. Still, there appears to be a significant negative link between the equity risk premium and government interest rates. The quarterly results in Table 7 would suggest about a 50 basis point change in risk premium for each 100 basis point movement in interest rates.

Overall, our ex ante estimates of the market risk premium are significantly linked to ex ante proxies for risk. Such a link suggests that investors modify their required returns in response to perceived changes in the environment. The findings provide some comfort that our risk premium estimates are capturing, at least in part, underlying economic changes in the economic environment. Moreover, each of the risk measures appears to contain relevant information for investors. The market risk premium is negatively related to the level of consumer confidence and positively linked to interest rate spreads between corporate and government debt, disagreement among analysts in their forecasts of earnings growth and the implied volatility of equity returns as revealed in options data.

II. Conclusions

Shareholder required rates of return and risk premia are based on theories about investors' expectations for the future. In practice, however, risk premia are typically estimated using averages of historical returns. This paper applies an alternate approach to estimating risk premia that employs publicly available expectational data. The resultant average market equity risk premium over government bonds is comparable in magnitude to long-term differences (1926 to 1998) in historical returns between stocks and bonds. As a result, our evidence does not resolve the equity premium puzzle; rather, our results suggest investors still expect to receive large spreads to invest in equity versus debt instruments.

There is strong evidence, however, that the market risk premium changes over time. Moreover, these changes appear linked to the level of interest rates as well as ex ante proxies for risk drawn from interest rate spreads in the bond market, consumer confidence in future economic conditions, disagreement among financial analysts in their forecasts and the volatility of equity returns implied by options data. The significant economic links between the market premium and a wide array of risk variables suggests that the notion of a constant risk premium over time is not an adequate explanation of pricing in equity versus debt markets.

Our results have implications for practice. First, at least on average, our estimates suggest a market premium roughly comparable to long-term historical spreads in returns between stocks and bonds. Our conjecture is that, if anything, our estimates are on the high side and thus establish an upper bound on the market premium. Second, our results suggest that use of a constant risk premium will not fully capture changes in investor return requirements. As a specific example, our findings indicate that common application of models such as the CAPM will overstate changes in shareholder return requirements when government interest rates change. Rather than a one-for-one change with interest rates implied by use of constant risk premium, our results indicate that equity required returns for average risk stocks likely change by half (or less) of the change in interest rates. However, the picture is considerably more complicated as shown by the linkages between the risk premium and other attributes of risk.

Ultimately, our research does not resolve the answer to the question "What is the right market risk premium?" Perhaps more importantly, our work suggests that the answer is conditional on a number of features in the economy—not an absolute. We hope that future research will harness ex ante data to provide additional guidance to best practice in using a market premium to improve financial decisions.

Table 1. Variable Definitions

k	=	Equity required rate return.
P_0	=	Price per share.
D_1	=	Expected dividend per share measured as current indicated annual dividend from COMPUSTAT multiplied by $(1 + g)$.
g	=	Average financial analysts' forecast of five-year growth rate in earnings per share (from IBES).
i	=	Yield to maturity on long-term U.S. government obligations (source: Federal Reserve, 30-year constant maturity series).
rp	=	Equity risk premium calculated as $rp = k - i$.
BSPREAD	=	spread between yields on corporate and government bonds, BSPREAD = yield to maturity on long-term corporate bonds (Moody's average across bond rating categories) minus i.
CON	=	Monthly consumer confidence index reported by the Conference Board (divided by 100).
DISP	=	Dispersion of analysts' forecasts at the market level.
VOL	=	Volatility for the SP500 index as implied by options data.

Table 2. Bond Market Yields, Equity Required Return, and Equity Risk Premium, 1982-1998

Values are averages of monthly figures in percent. i is the yield to maturity on long-term government bonds, k is the required return on the SP500 estimated as a value weighted average using a discounted cash flow model with analysts' growth forecasts. The risk premium $rp = k - i$. The average of analysts' growth forecasts is g. *Div yield* is expected dividend per share divided by price per share.

Year	*Div yield*	g	K	i	$rp = k - i$
1982	6.89	12.73	19.62	12.76	6.86
1983	5.24	12.60	17.86	11.18	6.67
1984	5.55	12.02	17.57	12.39	5.18
1985	4.97	11.45	16.42	10.79	5.63
1986	4.08	11.05	15.13	7.80	7.34
1987	3.64	11.01	14.65	8.58	6.07
1988	4.27	11.00	15.27	8.96	6.31
1989	3.95	11.08	15.03	8.45	6.58
1990	4.03	11.69	15.72	8.61	7.11
1991	3.64	11.99	15.63	8.14	7.50
1992	3.35	12.13	15.47	7.67	7.81
1993	3.15	11.63	14.78	6.60	8.18
1994	3.19	11.47	14.66	7.37	7.29
1995	3.04	11.51	14.55	6.88	7.67
1996	2.60	11.89	14.49	6.70	7.79
1997	2.18	12.60	14.78	6.60	8.17
1998	1.80	12.95	14.75	5.58	9.17
Average	3.86	11.81	15.67	8.53	7.14

Table 3. Average Historical Returns on Bonds, Stocks, Bills, and Inflation in the U.S., 1926-1998

Historical Return Realizations	Geometric Mean	Arithmetic Mean
Common Stock (large company)	11.2%	13.2%
Long-term government bonds	5.3%	5.7%
Treasury bills	3.8%	3.8%
Inflation rate	3.1%	3.2%

Source: Ibbotson Associates, Inc., *1999 Stocks, Bonds, Bills and Inflation*, 1999 Yearbook.

Table 4. Descriptive Statistics on Ex Ante Risk Measures

Entries are based on monthly data. BSPREAD is the spread between yields on long-term corporate and government bonds. CON is the consumer confidence index. DISP measures the dispersion of analysts' forecasts of earnings growth. VOL is the volatility on the SP500 index implied by options data. Variables are expressed in decimal form, e.g., 12% = .12.

A. Variable
Monthly Levels

	Mean	Standard Deviation	Minimum	Maximum
BSPREAD	.0123	.0040	.0070	.0254
CON	.9500	.2240	.473	1.382
DISP	.0349	.0070	.0285	.0687
VOL	.1599	.0696	.0765	.6085

B. Variable
Monthly Changes

	Mean	Standard Deviation	Minimum	Maximum
BSPREAD	-.00001	.0011	-.0034	.0036
CON	.0030	.0549	-.2300	.2170
DISP	-.00002	.0024	-.0160	.0154
VOL	-.0008	.0592	-.2156	.4081

C. Correlation Coefficients for Monthly Changes
*significantly different from zero at the .05 level
**significantly different from zero at the .01 level

	BSPREAD	CON	DISP	VOL
BSPREAD	1.00	-.16*	.05	.22**
CON	-.16*	1.00	.07	-.09
DISP	.05	.07	1.00	.03
VOL	.22**	-.09	.03	1.00

Table 5. Changes in the Market Equity Risk Premium Over Time

The table reports regression coefficients (t-values). Regression estimates use all variables expressed as monthly changes to correct for autocorrelation. The dependent variable is the market equity risk premium for the SP500 index. BSPREAD is the spread between yields on long-term corporate and government bonds. The yield to maturity on long-term government bonds is denoted as i. For purposes of the regression, variables are expressed in decimal form, e.g., 12% = .12.

Time period	Intercept	i	BSPREAD	R^2
A. 1982-1998	-.0002 (-1.49)	-.8696 (-16.54)		.57
	-.0002 (-1.11)	-.749 (-11.37)	.487 (2.94)	.59
B. 1980's	-.0005 (-1.62)	-.887 (-10.97)		.56
	-.0004 (-1.24)	-.759 (-7.42)	.508 (1.99)	.57
C. 1990's	-.0000 (-0.09)	-.840 (-13.78)		.64
	-.0000 (0.01)	-.757 (-9.85)	.347 (1.76)	.65

Table 6. Changes in the Market Equity Risk Premium Over Time and Selected Measures of Risk

The table reports regression coefficients (*t*-values). Regression estimates use all variables expressed as monthly changes to correct for autocorrelation. The dependent variable is the market equity risk premium for the SP500 index. BSPREAD is the spread between yields on long-term corporate and government bonds. The yield to maturity on long-term government bonds is denoted as *i*. CON is the change in consumer confidence index. DISP measures the dispersion of analysts' forecasts of earnings growth. VOL is the volatility on the SP500 index implied by options data. For purposes of the regression, variables are expressed in decimal form, e.g., 12% = .12.

Time period		Intercept	*i*	BSPREAD	CON	DISP	VOL	*Adj.* R^2
A. 1982-1998								
	(1)	0.0002 (.97)			-0.014 (-3.50)			0.05
	(2)	-0.0001 (-.96)	-0.737 (-11.31)	0.453 (2.76)	-0.007 (-2.48)			0.60
	(3)	0.0002 (.78)				0.244 (2.38)		0.02
	(4)	-0.0001 (-.93)	-0.733 (-11.49)	0.433 (2.69)	-0.007 (-2.77)	0.185 (3.13)		0.62
B. May 1986-1998								
	(5)	0.0000 (.03)	-0.821 (-11.16)	0.413 (2.47)	-0.005 (-2.22)	0.376 (3.74)		0.68
	(6)	0.0001 (.53)					0.011 (2.89)	0.05
	(7)	0.0000 (.02)	-0.831 (-11.52)	0.326 (1.95)	-0.005 (-2.12)	0.372 (3.77)	0.006 (2.66)	0.69

Table 7. Regressions Using Alternate Measures of Risk Premia to Analyze Potential Effects of Reporting Lags in Analysts' Forecasts

The table reports regression coefficients (t-values). Regression estimates use all variables expressed as changes (monthly or quarterly) to correct for autocorreclation. BSPREAD is the spread between yields on long-term corporate and government bonds. rp is the risk premium on the SP500 index. The yield to maturity on long-term government bonds is denoted as i. For purposes of the regression, variables are expressed in decimal form, e.g., 12% = .12.

Dependent Variable	Intercept	i	BSPREAD	*Adj.* R^2
(1) Equity Risk Premium (*rp*) Monthly Observations (same as Table 5)	-.0002 (-1.11)	-.749 (-11.37)	.487 (2.94)	.59
(2) Equity Risk Premium (*rp*) "Quarterly" nonoverlapping observations to account for lags in analyst reporting	-.0002 (-.49)	-.527 (-6.18)	.550 (2.20)	.60
(3) Corporate Bond Spread (BSPREAD) Monthly Observations	-.0001 (-1.90)	-.247 (-11.29)		.38

REFERENCES

R.B. Boebel, "The Information Content of Financial Analysts' Forecasts: Short-term vs. Long-term," University of North Carolina at Chapel Hill, Dissertation, 1991. University Microfilms International order number 9207936.

R.B. Boebel, M.N. Gultekin and R.S. Harris, "Financial Analysts' Forecast of Corporate Earnings Growth: Top Down Versus Bottom Up," in *Handbook of Security Analyst Forecasting and Asset Allocation*, John B. Guerard, Jr. and Mustafa N. Gultekin (eds.), London, JAI Press, 1993, pp. 185-192.

D. Brigham, D. Shome, and S. Vinson, "The Risk Premium Approach to Measuring A Utility's Cost of Equity," *Financial Management* (Spring 1985), pp. 33-45.

L.D. Brown, " Earnings Forecasting Research: Its Implications for Capital Market Research," *International Journal of Forecasting* (November 1993), pp. 295-320.

L.D. Brown, "Analyst Forecasting Errors: Additional Evidence," *Financial Analysts Journal* (November/December 1997), pp. 81-90.

R.F. Bruner, K. Eades, R. Harris and R. Higgins, Best Practices in Estimating the Cost of Capital: Survey and Synthesis," *Financial Practice and Education* (Spring/Summer 1998), pp. 13-28.

W.T. Carleton and J. Lakonishok, "Risk and Return on Equity: The Use and Misuse of Historical Estimates," *Financial Analysts Journal* (January/February 1985), pp. 38-47.

L. Chan, Y. Hamao, and J. Lakonishok, "Fundamental and Stock Returns in Japan," *Journal of Finance*, 46, (5), (December 1991) pp. 1739-64.

J. Cragg and B.G. Malkiel, *Expectations and the Structure of Share Prices*, National Bureau of Economic Research, Chicago, University of Chicago Press, 1982.

Goldman Sachs, *EVA Company Analysis*, January 1999.

R.S. Harris, "Using Analysts' Growth Forecasts to Estimate Shareholder Required Rates of Return," *Financial Management* (Spring 1988), pp. 58-67.

Ibbotson Associates, Inc., *1998 Cost of Capital Quarterly*, 1998 Yearbook

Ibbotson Associates, Inc., *1997 Stocks, Bonds, Bills, and Inflation*, 1997 Yearbook.

J. Johnston, *Econometric Methods*, New York, McGraw-Hill, 3rd edition, 1984.

P. Kennedy, *A Guide to Econometrics*, Cambridge, MIT Press, 2nd edition, 1985.
G.S. Madalla, *Econometrics*, New York, McGraw-Hill, 1977.

B. Malkiel, "Risk and Return: A New Look," in *The Changing Role of Debt and Equity in Financing U.S. Capital Formation*, B.B. Friedman (ed.), National Bureau of Economic Research, Chicago, University of Chicago Press, 1982.

B. Malkiel, "The Capital Formation Problem in the United States," *Journal of Finance* (May 1979), pp. 291-306.

F. Marston, R. Harris, and P. Crawford, "Risk and Return in Equity Markets: Evidence Using Financial Analysts' Forecasts," in *Handbook of Security Analysts' Forecasting and Asset Allocation*, J. Guerard and M. Gultekin (eds.), Greenwich, CT, JAI Press, 1992, pp. 101-122.

F. Marston and R.S. Harris, "Risk, Return, and Equilibrium: A Revisit Using Expected Returns," *Financial Review*, (February 1993).

J. Siegel and R. Thaler, "Anomalies: The Equity Premium Puzzle," *Journal of Economic Perspectives*, 11 (1), (1997), pp. 191-200.

J. VanderWeide and W.T. Carleton, "Investor Growth Expectations: Analysts vs. History," *Journal of Portfolio Management* (Spring 1988), pp. 78-82.

I. Welch, "Views of Financial Economists on the Equity Premium and Other Issues," UCLA/Anderson Finance Working Paper 10-98, May 18, 1998.

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THE MARKET RISK PREMIUM:
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The Market Risk Premium: Expectational Estimates Using Analysts' Forecasts

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The Market Risk Premium: Expectational Estimates Using Analysts' Forecasts

Abstract

We use expectational data from financial analysts to estimate a market risk premium for U.S. stocks. Using the SP500 as a proxy for the market portfolio, we find an average market risk premium of 7.14% above yields on long-term U.S. government bonds over the period 1982-1998. We also find that this risk premium varies over time and that much of this variation can be explained by either the level of interest rates or readily available forward-looking proxies for risk. The market risk premium appears to move inversely with government interest rates suggesting that required returns on stocks are more stable than interest rates themselves.

The Market Risk Premium: Expectational Estimates Using Analysts' Forecasts

The notion of a market risk premium (the spread between investor required returns on safe and average risk assets) has long played a central role in finance. It is a key factor in asset allocation decisions to determine the portfolio mix of debt and equity instruments. Moreover, the market risk premium plays a critical role in the Capital Asset Pricing Model (CAPM), practitioners most widely used means of estimating equity hurdle rates. In recent years, the practical significance of estimating such a market premium has increased as firms, financial analysts and investors employ financial frameworks to analyze corporate and investment performance. For instance, the increased use of Economic Value Added to assess corporate performance has provided a new impetus for estimating capital costs.

The most prevalent approach to estimating the market risk premium relies on some average of the historical spread between returns on stocks and bonds.[1] This choice has some appealing characteristics but is subject to many arbitrary assumptions such as the relevant period for taking an average. Compounding the difficulty of using historical returns is the well noted fact that standard models of consumer choice would predict much lower spreads between equity and debt returns than have occurred in U.S. markets—the so called equity premium puzzle (see Welch (1998), Siegel and Thaler (1997)). In addition, theory calls for a forward looking risk premium that could well change over time.

[1] Bruner, Eades, Harris and Higgins (1998) provide survey evidence on both textbook advice and practitioner methods for estimating capital costs. Despite substantial empirical assault, the CAPM continues to play a major role in applied finance. As testament to the market for cost of capital estimates Ibbotson Associates (1998) publishes a "Cost of Capital Quarterly."

This paper takes an alternate approach by using expectational data to estimate the market risk premium. The approach has two major advantages for practitioners. First, it provides an independent estimate which can be compared to historical averages. At a minimum, this can help in understanding likely ranges for risk premia. Second, expectational data allow investigation of changes in risk premia over time. Such time variations in risk premia serve as important signals from investors that should affect a host of financial decisions.

The paper updates and extends earlier work (Harris (1986), Harris and Marston (1992)) which incorporates financial analysts' forecasts of corporate earnings growth. Updating through 1998 provides an opportunity to see whether changes in the risk premium are in part responsible for the run up in share prices in the bull market. In addition, we provide new tests of whether changes in risk premia over time are linked to forward-looking measures of risk. Specifically, we look at the relationship between the risk premium and four ex-ante measures of risk: the spread between yields on corporate and government bonds, consumer sentiment about future economic conditions, the average level of dispersion across analysts as they forecast corporate earnings and the implied volatility on the SP500 Index derived from options data.

Section I provides background on the estimation of equity required returns and a brief discussion of current practice in estimating the market risk premium. In Section II, models and data are discussed. Following a comparison of the results to historical returns in Section III, we examine the time-series characteristics of the estimated market premium in Section IV. Finally, conclusions are offered in Section V.

I. Background

The notion of a "market" required rate of return is a convenient and widely used construct. Such a rate (k) is the minimum level of expected return necessary to compensate investors for bearing the average risk of equity investments and receiving dollars in the future rather than in the present. In general, k will depend on returns available on alternative investments (e.g., bonds). To isolate the effects of risk, it is useful to work in terms of a market risk premium (*rp*), defined as

$$rp = k - i, \tag{1}$$

where i = required return for a zero risk investment.

Lacking a superior alternative, investigators often use averages of historical realizations to estimate a market risk premium. Bruner *et al.* (1998) provide recent survey results on best practices by corporations and financial advisors. While almost all respondents used some average of past data in estimating a market risk premium, a wide range of approaches emerged. "While most of our 27 sample companies appear to use a 60+- year historical period to estimate returns, one cited a window of less than ten years, two cited windows of about ten years, one began averaging with 1960, and another with 1952 data" (p. 22). Some used arithmetic averages and some geometric. This historical approach requires the assumptions that past realizations are a good surrogate for future expectations and, as typically applied, that the risk premium is constant over time. Carleton and Lakonishok (1985) demonstrate empirically some of the problems with such historical premia when they are dissaggregated for different time periods or groups of firms. As Bruner *et al* (1998) point out, few respondents cited use of expectational data to supplement or replace historical returns in estimating the market premium.

Survey evidence also shows substantial variation in empirical estimates. When respondents gave a precise estimate of the market premium, they cited figures from 4 to over 7 percent (Bruner *et al* 1998). A quote from a survey respondent highlights the range in practice. "In 1993, we polled various investment banks and academic studies on the issue as to the appropriate rate and got anywhere between 2 and 8%, but most were between 6 and 7.4%." (Bruner *et al* 1998, p. 23). An informal sampling of current practice also reveals large differences in assumptions about an appropriate market premium. For instance, in a 1999 application of EVA analysis, Goldman Sachs Investment Research specifies a market risk premium of "3%

from 1994-1997 and 3.5% from 1998-1999E for the S&P Industrials" (Goldman Sachs (1999, p. 59)). At the same time an April 1999 phone call to Stern Stewart revealed that their own application of EVA typically employed a market risk premium of 6%. In its application of the CAPM, Ibbotson Associates (1998) uses a market risk premium of 7.8%. Not surprisingly, academics don't agree on risk premium either. Welch (1998) surveyed leading financial economists at major universities. For a 30-year horizon, he found a mean risk premium of 6.12% but a range from 2% to 9% with an interquartile range of 2% (based on 104 responses).

To provide additional insight on estimates of the market premium, we use publicly available expectational data. This expectational approach employs the dividend growth model (hereafter referred to as the discounted cash flow or DCF model) in which a consensus measure of financial analysts' forecasts (FAF) of earnings is used as a proxy for investor expectations. Earlier works by Malkiel (1982), Brigham, Vinson, and Shome (1985), Harris (1986) and Harris and Marston (1992) have used FAF in DCF models[2].

II. Models and Data

We employ the simplest and most commonly used version of the DCF model to estimate shareholders' required rate of return, k, as shown in Equation (2):

$$k = \left(\frac{D_1}{P_0}\right) + g, \tag{2}$$

where D_1 = dividend per share expected to be received at time one, P_0 = current price per share (time 0), and g = expected growth rate in dividends per share[3]. A primary difficulty in using the

[2] Ibbotson Associates (1998) use a variant of the DCF model with forward-looking growth rates as one means to estimate cost of equity; however, they do this as a separate technique and not as part of the CAPM. For their CAPM estimates they use historical averages for the market risk premium. The DCF approach with analysts' forecasts has been used frequently in regulatory settings.

[3] Our methods follow Harris (1986) and Harris and Marston (1992) who provide an overview of earlier research and a detailed discussion of the approach employed here. For instance, theoretically, i is a risk-free rate, though empirically its proxy (e.g., yield to maturity on a government bond) is only a "least risk" alternative that is itself subject to risk. They also discuss single versus multistage growth discounted cash flow models and procedures used in calculating the expected dividend yield. While the model calls for expected growth in dividends, in the long run, dividend growth is sustainable only via growth in earnings. As long as payout ratios are not expected to change, the two growth rates will be the same.

DCF model is obtaining an estimate of g, since it should reflect market expectations of future performance. This paper uses published FAF of long-run growth in earnings as a proxy for g. Equation (2) can be applied for an individual stock or any portfolio of companies. We focus primarily on its application to estimate a market premium as proxied by the SP500.

FAF come from IBES Inc. The mean value of individual analysts' forecasts of five-year growth rate in EPS is used as our estimate of g in the DCF model. The five-year horizon is the longest horizon over which such forecasts are available from IBES and often is the longest horizon used by analysts. IBES requests "normalized" five-year growth rates from analysts in order to remove short-term distortions that might stem from using an unusually high or low earnings year as a base. Growth rates are available on a monthly basis.

Dividend and other firm-specific information come from COMPUSTAT. D_1 is estimated as the current indicated annual dividend times (1+g). Interest rates (both government and corporate) are gathered from Federal Reserve Bulletins and *Moody's Bond Record*. Table 1 describes key variables used in the study. Data are collected for all stocks in the Standard & Poor's 500 stock (SP500) index followed by IBES. Since five-year growth rates are first available from IBES beginning in 1982, the analysis covers the period from January 1982-December 1998.

We generally adopt the same approach as used in Harris and Marston (1992). For each month, a market required rate of return is calculated using each dividend paying stock in the SP500 index for which data are available. As additional screens for reliability of data, in a given month we eliminate a firm if there are fewer than three analysts' forecasts or if the standard deviation around the mean forecast exceeds 20%. Combined these two screens eliminate fewer than 20 stocks a month. Later we report on the sensitivity of our results to various screens. The DCF model in Equation (2) is applied to each stock and the results weighted by market value of equity to produce the market-required return.[4] The risk premium is constructed by subtracting the interest rate on government bonds.

For short-term horizons (quarterly and annual), past research (Brown, 1993) finds that on average analysts' forecasts are overly optimistic compared to realizations. However, recent research on quarterly horizons (Brown, 1997) suggests that analysts' forecasts for SP500 firms do not have an optimistic bias for the period 1993-1996. There is very little research on the properties of five-year growth forecasts, as opposed to shorter horizon predictions.[5] Any analysts' optimism is not necessarily a problem for our analysis. If investors share analysts' views, our procedures will still yield unbiased estimates of required returns and risk premia. In light of the possible bias, however, we interpret our estimates as "upper bounds" for the market premium.

To broaden our exploration, we tap four very different sources to create ex ante measures of equity risk at the market level. The first proxy comes from the bond market and is calculated as the spread between corporate and government bond yields (BSPREAD). The rationale is that increases in this spread signal investors' perceptions of increased riskiness of corporate activity that would be translated to both debt and equity owners. The second measure, CON, is the consumer confidence index reported by the Conference Board at the end of the month. While the reported index tends to be around 100, we rescale CON as the actual index divided by 100. We also examined use of CON as of the end of the prior month; however, in regression analysis

[4] We weighted 1998 results by year-end 1997 market values since our monthly data on market value did not extend through this period. Since we did not have data on firm-specific dividend yields for the last four months of 1998, we estimated the market dividend yield for these months using the dividend yield reported in the *Wall Street Journal* scaled by the average ratio of this figure to the dividend yield for our sample as calculated in the first eight months of 1998. We then made adjustments using growth rates from IBES to calculate the market required return. We also estimated results using an average dividend yield for the month which employed the average of the price at the end of the current and prior months. These average dividend yield measures led to essentially the same regression coefficients as those reported later in the paper but introduced significant serial correlation in some regressions (Durbin-Watson statistics significantly different from 2.0 at the .01 level).

[5] To our knowledge, the only studies of possible bias in analysts' five-year growth rates are Boebel (1991) and Boebel, Harris and Gultekin (1993). They both find evidence of optimism in IBES growth forecasts. In the most thorough study to date, Boebel (1991) reports that this bias seems to be getting smaller over time. His forecast data do not extend into the 1990's.

this lagged measure was generally not statistically significant in explaining the level of the market risk premium[6]. The third measure, DISP, measures the dispersion of analysts' forecasts. Such analyst disagreement should be positively related to perceived risk since higher levels of uncertainty would likely generate a wider distribution of earnings forecasts for a given firm. DISP is calculated as the equally weighted average of firm-specific standard deviations for each stock in the SP500 covered by IBES. The firm-specific standard deviation is calculated based on the dispersion of individual analysts' growth forecasts around the mean of individual forecasts for that company in that month. Our final measure, VOL, is the implied volatility on the SP500 index. As of the beginning of the month, we use a dividend adjusted Black Scholes Formula to estimate the implied volatility in the SP500 index option contract which expires on the third Friday of the month. The call premium, exercise price and the level of the SP500 index are taken from the *Wall Street Journal* and treasury yields come from the Federal Reserve. Dividend yield comes from DRI. We use the option contract that is closest to being at the money.

III. Estimates of the Market Premium

Table 2 reports both required returns and risk premia by year (averages of monthly data). The results are quite consistent with the patterns reported earlier (e.g., Harris and Marston, 1992). The estimated risk premia are positive, consistent with equity owners demanding additional rewards over and above returns on debt securities. The average expectational risk premium (1982 to 1998) over government bonds is 7.14%, slightly higher than the 6.47% average for 1982 to 1991 reported earlier (Harris and Marston, 1992). For comparison purposes, Table 3 contains historical returns and risk premia. The average expectational risk premium

[6] We examined two other proxies for Consumer Confidence. The Conference Board's Consumer Expectations Index yielded essentially the same results as those reported. The University of Michigan's Consumer Sentiment Indices tended to be less significantly linked to the market risk premium though coefficients were still negative.

reported in Table 2 is approximately equal to the arithmetic (7.5%) long-term differential between returns on stocks and long-term government bonds.[7]

Table 2 shows the estimated risk premium changes over time, suggesting changes in the market's perception of the incremental risk of investing in equity rather than debt securities. Scanning the next to last column of Table 2, the risk premium is higher in the 1990's than earlier and especially so in late 1997 and 1998. Our DCF results provide no evidence to support the notion of a declining risk premium in the 1990's as a driver of the strong run up in equity prices.

A striking feature in Table 2 is the relative stability of our estimates of *k*. After dropping (along with interest rates) in the early and mid-1980's, the average annual value of *k* has remained within a 75 basis point range around 15 percent for over a decade. Moreover, this stability arises despite some variability in the underlying dividend yield and growth components of *k* as Table 2 illustrates. The results suggest that *k* is more stable than government interest rates. Such relative stability of *k* translates into parallel changes in the market risk premium. In a subsequent section, we examine whether changes in our market risk premium estimates appear linked to interest rate conditions and a number of proxies for risk[8].

We explored the sensitivity of our results to our screening procedures in selecting companies. Our reported results screen out all non-dividend paying stocks on the premise that use of the DCF model is inappropriate in such cases. The dividend screen eliminates an average of 55 companies per month. In a given month, we also screen out firms with fewer than three analysts' forecasts, or if the standard deviation around the mean forecast exceeds 20%. When we repeated our analysis without any of the screens, the average risk premium over the sample

[7] Interestingly, for the 1982-1996 period the arithmetic spread between large company stocks and long-term government bonds was only 3.3% per year. The downward trend in interest rates resulted in average annual returns of 14.1% on long-term government bonds over this horizon. Some (e.g., Ibbotson, 1997) argue that only the income (not total) return on bonds should be subtracted in calculating risk premia.

[8] Although our focus is on the market risk premium, in earlier work (Harris and Marston (1992), Marston, Harris and Crawford (1993)), we examined the cross-sectional link between expectational equity risk premia at the firm level and beta and found a significant positive correlation. For comparative purposes, we replicated and updated that

period increased by only 40 basis points, from 7.14% to 7.54%. We also estimated the beta of our sample firms and found the sample average to be one, suggesting that our screens do not systematically remove low or high-risk firms. Specifically, using firms in our screened sample as of December 1997 (the last date for which we had CRSP return data), we used ordinary least squares regressions to estimate beta for each stock using the prior sixty months of data and the CRSP return (SPRTRN) as the market index. The value-weighted average of the individual betas was 1.00.

In the results reported here we use firms in the SP500 as reported by COMPUSTAT in September 1998 which could create a survivorship bias, especially in the earlier months of our sample. We compared our current results to those obtained in our earlier work (Harris and Marston (1992)) for which we had data to update the SP500 composition each month. For the overlapping period, January 1982-May 1991 the two procedures yield the same average market risk premium, 6.47%. This suggests that the firms departing from or entering the SP500 index do so for a number of reasons with no discernable effect on the overall estimated SP500 market risk premium.

IV. Changes in the Market Risk Premium Over Time

With changes in the economy and financial markets, equity investments may be perceived to change in risk. For instance, investor sentiment about future business conditions likely affects attitudes about the riskiness of equity investments compared to investments in the bond markets. Moreover, since bonds are risky investments themselves, equity risk premia (relative to bonds) could change due to changes in perceived riskiness of bonds, even if equities displayed no shifts in risk.

In earlier work covering the 1982-1991 period, Harris and Marston (1992) reported regression results indicating that the market premium decreased with the level of government

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analysis through 1998 and reached very similar conclusions. At the firm level our expectational estimates of risk interest rates and increased with the spread between corporate and government bond yields (BSPREAD). This bond yield spread was interpreted as a time series proxy for equity risk. We introduce three additional ex ante measures of risk shown in Table 1: CON, DISP and VOL. The three measures come from three independent sets of data and are supplied by different agents in the economy (consumers, equity analysts and investors (via option and share price data)). Table 4 provides summary data on all four of our risk measures.

Table 5 replicates and updates earlier analysis.[9] The results confirm the earlier patterns. For the entire sample period, Panel A shows that risk premia are negatively related to interest rates. This negative relationship is also true for both the 1980's and 1990's as displayed in Panels B and C. For the entire 1982 to 1998 period, the addition of the yield spread risk proxy to the regressions lowers the magnitude of the coefficient on government bond yields, as can be seen by comparing Equations 1 and 2 of Panel A. Furthermore, the coefficient of the yield spread (0.487) is itself significantly positive. This pattern suggests that a reduction in the risk differential between investment in government bonds and in corporate activity is translated into a lower equity market risk premium.

In major respects, the results in Table 5 parallel earlier findings. The market risk premium changes over time and appears inversely related to government interest rates but positively related to the bond yield spread, which proxies for the incremental risk of investing in equities as opposed to government bonds. One striking feature is the large negative coefficients on government bond yields. The coefficients indicate the equity risk premium declines by over 70 basis points for a 100 basis point increase in government interest rates.[10] This inverse

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premia are significantly positively correlated to beta.

[9] OLS regressions with levels of variables generally showed severe autocorrelation. As a result, we used the Prais-Winsten method (on levels of variables) and also OLS regressions on first differences of variables. Since both methods yielded similar results and the latter had more stable coefficients across specifications, we report only the results using first differences. Tests using Durbin-Watson statistics from regressions in Tables 5 and 6 do not accept the hypothesis of autocorrelated errors (tests at .01 significance level, see Johnston 1984, pp. 321-325).

[10] The Table 5 coefficients on i are significantly different from -1.0 suggesting that equity required returns do respond to interest rate changes. However, the large negative coefficients imply only minor adjustments of required

relationship suggests much greater stability in equity required returns than is often assumed. For instance, standard application of the CAPM suggests a one-to-one change in equity returns and government bond yields.

Table 6 introduces three additional proxies for risk and explores whether these variables, either individually or collectively, are correlated with the market premium. Since our estimates of implied volatility start in May 1986, the table shows results for both the entire sample period and for the period during which we can introduce all variables. Entered individually each of the three variables is significantly linked to the risk premium with the coefficient having the expected sign. For instance, in regression (1) the coefficient on CON is -.014 which is significantly different from zero (t = -3.50). The negative coefficient signals that higher consumer confidence is linked to a lower market premium. The positive coefficients on VOL and DISP indicate the equity risk premium increases with both market volatility and disagreement among analysts. The effects of the three variables appear largely unaffected by adding other variables. For instance, in regression (4) the coefficients on CON and DISP both remain significant and are similar in magnitude to the coefficients in single variable regressions.

Even in the presence of the new risk variables, Table 6 shows that the market risk premium is affected by interest rate conditions. The large negative coefficient on government bond rates implies large reductions in the equity premium as interest rates rise. One feature of our data may contribute to the observed negative relationship between the market risk premium and the level of interest rates. Specifically, if analysts are slow to report updates in their growth forecasts, changes in our estimated *k* would not adjust fully with changes in the interest rate even if the true risk premium were constant. To address the impact of "stickiness" in the measurement of *k*, we formed "quarterly" measures of the risk premium which treat *k* as an average over the

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returns to interest rate changes since the risk premium declines. In earlier work (Harris and Marston (1991)) the coefficient was significantly negative but not as large in absolute value. In that earlier work we reported results quarter. Specifically, we take the value of k at the end of a quarter and subtract from it the average value of i for the months ending when k is measured. For instance, to form the risk premium for March 1998 we take the March value of k and subtract the average value of i for January, February and March. This approach assumes that in March k still reflects values of g that have not been updated from the prior two months. We then pair our quarterly measure of risk premium with the average values of the other variables for the quarter. For instance, the March 1998 "quarterly" risk premium would be paired with averaged values of BSPREAD over the January through March period. To avoid overlapping observations for the independent variables, we use only every third month (March, June, September, December) in the sample.

As reported in Table 7, sensitivity analysis using "quarterly" observations suggests that delays in updating may be responsible for a portion, but not all, of the observed negative relationship between the market premium and interest rates. For example, when we use quarterly observations the coefficient on i in regression (2) of Table 7 is -.527, well below the earlier estimates but still significantly negative[11].

As an additional test, we look at movements in the bond risk premium (BSPREAD). Since BSPREAD is constructed directly from bond yield data it does not have the potential for reporting lags that may affect analysts' growth forecasts. Regression 3 in Table 7 shows BSPREAD is negatively linked to government rates and significantly so[12]. While the equity premium need not move in the same pattern as the corporate bond premium, the negative coefficient on BSPREAD suggests that our earlier results are not due solely to "stickiness" in measurements of market required returns.

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using the Prais-Winsten estimators. When we use that estimation technique and recreate the second regression in Table 5, the coefficient for i is -.584 (t = 12.23) for the entire sample period 1982-1998.

[11] Sensitivity analysis for the 1982-1989 and 1990-1998 subperiods yields results similar to those reported.

[12] We thank Bob Conroy for suggesting use of BSPREAD. Regression 3 in Table 7 appears to have autocorrelated errors: the Durbin-Watson (DW) statistic rejects the hypothesis of no autocorrelation. However, in subperiod analysis, the DW statistic for the 1990-98 period is consistent with no autocorrelation and the coefficient on i is essentially the same (-.24, t = -8.05) as reported in Table 7.

The results in Table 7 suggest that the inverse relationship between interest rates and the market risk premium may not be as pronounced as suggested in earlier tables. Still, there appears to be a significant negative link between the equity risk premium and government interest rates. The quarterly results in Table 7 would suggest about a 50 basis point change in risk premium for each 100 basis point movement in interest rates.

Overall, our ex ante estimates of the market risk premium are significantly linked to ex ante proxies for risk. Such a link suggests that investors modify their required returns in response to perceived changes in the environment. The findings provide some comfort that our risk premium estimates are capturing, at least in part, underlying economic changes in the economic environment. Moreover, each of the risk measures appears to contain relevant information for investors. The market risk premium is negatively related to the level of consumer confidence and positively linked to interest rate spreads between corporate and government debt, disagreement among analysts in their forecasts of earnings growth and the implied volatility of equity returns as revealed in options data.

II. Conclusions

Shareholder required rates of return and risk premia are based on theories about investors' expectations for the future. In practice, however, risk premia are typically estimated using averages of historical returns. This paper applies an alternate approach to estimating risk premia that employs publicly available expectational data. The resultant average market equity risk premium over government bonds is comparable in magnitude to long-term differences (1926 to 1998) in historical returns between stocks and bonds. As a result, our evidence does not resolve the equity premium puzzle; rather, our results suggest investors still expect to receive large spreads to invest in equity versus debt instruments.

There is strong evidence, however, that the market risk premium changes over time. Moreover, these changes appear linked to the level of interest rates as well as ex ante proxies for risk drawn from interest rate spreads in the bond market, consumer confidence in future economic conditions, disagreement among financial analysts in their forecasts and the volatility of equity returns implied by options data. The significant economic links between the market premium and a wide array of risk variables suggests that the notion of a constant risk premium over time is not an adequate explanation of pricing in equity versus debt markets.

Our results have implications for practice. First, at least on average, our estimates suggest a market premium roughly comparable to long-term historical spreads in returns between stocks and bonds. Our conjecture is that, if anything, our estimates are on the high side and thus establish an upper bound on the market premium. Second, our results suggest that use of a constant risk premium will not fully capture changes in investor return requirements. As a specific example, our findings indicate that common application of models such as the CAPM will overstate changes in shareholder return requirements when government interest rates change. Rather than a one-for-one change with interest rates implied by use of constant risk premium, our results indicate that equity required returns for average risk stocks likely change by half (or less) of the change in interest rates. However, the picture is considerably more complicated as shown by the linkages between the risk premium and other attributes of risk.

Ultimately, our research does not resolve the answer to the question "What is the right market risk premium?" Perhaps more importantly, our work suggests that the answer is conditional on a number of features in the economy—not an absolute. We hope that future research will harness ex ante data to provide additional guidance to best practice in using a market premium to improve financial decisions.

Table 1. Variable Definitions

k	=	Equity required rate return.
P_0	=	Price per share.
D_1	=	Expected dividend per share measured as current indicated annual dividend from COMPUSTAT multiplied by $(1 + g)$.
g	=	Average financial analysts' forecast of five-year growth rate in earnings per share (from IBES).
i	=	Yield to maturity on long-term U.S. government obligations (source: Federal Reserve, 30-year constant maturity series).
rp	=	Equity risk premium calculated as $rp = k - i$.
BSPREAD	=	spread between yields on corporate and government bonds, BSPREAD = yield to maturity on long-term corporate bonds (Moody's average across bond rating categories) minus i.
CON	=	Monthly consumer confidence index reported by the Conference Board (divided by 100).
DISP	=	Dispersion of analysts' forecasts at the market level.
VOL	=	Volatility for the SP500 index as implied by options data.

Table 2. Bond Market Yields, Equity Required Return, and Equity Risk Premium, 1982-1998

Values are averages of monthly figures in percent. i is the yield to maturity on long-term government bonds, k is the required return on the SP500 estimated as a value weighted average using a discounted cash flow model with analysts' growth forecasts. The risk premium $rp = k - i$. The average of analysts' growth forecasts is g. *Div yield* is expected dividend per share divided by price per share.

Year	*Div yield*	g	K	i	$rp = k - i$
1982	6.89	12.73	19.62	12.76	6.86
1983	5.24	12.60	17.86	11.18	6.67
1984	5.55	12.02	17.57	12.39	5.18
1985	4.97	11.45	16.42	10.79	5.63
1986	4.08	11.05	15.13	7.80	7.34
1987	3.64	11.01	14.65	8.58	6.07
1988	4.27	11.00	15.27	8.96	6.31
1989	3.95	11.08	15.03	8.45	6.58
1990	4.03	11.69	15.72	8.61	7.11
1991	3.64	11.99	15.63	8.14	7.50
1992	3.35	12.13	15.47	7.67	7.81
1993	3.15	11.63	14.78	6.60	8.18
1994	3.19	11.47	14.66	7.37	7.29
1995	3.04	11.51	14.55	6.88	7.67
1996	2.60	11.89	14.49	6.70	7.79
1997	2.18	12.60	14.78	6.60	8.17
1998	1.80	12.95	14.75	5.58	9.17
Average	3.86	11.81	15.67	8.53	7.14

Table 3. Average Historical Returns on Bonds, Stocks, Bills, and Inflation in the U.S., 1926-1998

Historical Return Realizations	Geometric Mean	Arithmetic Mean
Common Stock (large company)	11.2%	13.2%
Long-term government bonds	5.3%	5.7%
Treasury bills	3.8%	3.8%
Inflation rate	3.1%	3.2%

Source: Ibbotson Associates, Inc., *1999 Stocks, Bonds, Bills and Inflation*, 1999 Yearbook.

Table 4. Descriptive Statistics on Ex Ante Risk Measures

Entries are based on monthly data. BSPREAD is the spread between yields on long-term corporate and government bonds. CON is the consumer confidence index. DISP measures the dispersion of analysts' forecasts of earnings growth. VOL is the volatility on the SP500 index implied by options data. Variables are expressed in decimal form, e.g., 12% = .12.

A. Variable Monthly Levels

	Mean	Standard Deviation	Minimum	Maximum
BSPREAD	.0123	.0040	.0070	.0254
CON	.9500	.2240	.473	1.382
DISP	.0349	.0070	.0285	.0687
VOL	.1599	.0696	.0765	.6085

B. Variable Monthly Changes

	Mean	Standard Deviation	Minimum	Maximum
BSPREAD	-.00001	.0011	-.0034	.0036
CON	.0030	.0549	-.2300	.2170
DISP	-.00002	.0024	-.0160	.0154
VOL	-.0008	.0592	-.2156	.4081

C. Correlation Coefficients for Monthly Changes
*significantly different from zero at the .05 level
**significantly different from zero at the .01 level

	BSPREAD	CON	DISP	VOL
BSPREAD	1.00	-.16*	.05	.22**
CON	-.16*	1.00	.07	-.09
DISP	.05	.07	1.00	.03
VOL	.22**	-.09	.03	1.00

Table 5. Changes in the Market Equity Risk Premium Over Time

The table reports regression coefficients (*t*-values). Regression estimates use all variables expressed as monthly changes to correct for autocorrelation. The dependent variable is the market equity risk premium for the SP500 index. BSPREAD is the spread between yields on long-term corporate and government bonds. The yield to maturity on long-term government bonds is denoted as *i*. For purposes of the regression, variables are expressed in decimal form, e.g., 12% = .12.

Time period	Intercept	*i*	BSPREAD	R^2
A. 1982-1998	-.0002 (-1.49)	-.8696 (-16.54)		.57
	-.0002 (-1.11)	-.749 (-11.37)	.487 (2.94)	.59
B. 1980's	-.0005 (-1.62)	-.887 (-10.97)		.56
	-.0004 (-1.24)	-.759 (-7.42)	.508 (1.99)	.57
C. 1990's	-.0000 (-0.09)	-.840 (-13.78)		.64
	-.0000 (0.01)	-.757 (-9.85)	.347 (1.76)	.65

Table 6. Changes in the Market Equity Risk Premium Over Time and Selected Measures of Risk

The table reports regression coefficients (*t*-values). Regression estimates use all variables expressed as monthly changes to correct for autocorrelation. The dependent variable is the market equity risk premium for the SP500 index. BSPREAD is the spread between yields on long-term corporate and government bonds. The yield to maturity on long-term government bonds is denoted as *i*. CON is the change in consumer confidence index. DISP measures the dispersion of analysts' forecasts of earnings growth. VOL is the volatility on the SP500 index implied by options data. For purposes of the regression, variables are expressed in decimal form, e.g., 12% = .12.

Time period		Intercept	*i*	BSPREAD	CON	DISP	VOL	*Adj.* R^2
A. 1982-1998								
	(1)	0.0002 (.97)			-0.014 (-3.50)			0.05
	(2)	-0.0001 (-.96)	-0.737 (-11.31)	0.453 (2.76)	-0.007 (-2.48)			0.60
	(3)	0.0002 (.78)				0.244 (2.38)		0.02
	(4)	-0.0001 (-.93)	-0.733 (-11.49)	0.433 (2.69)	-0.007 (-2.77)	0.185 (3.13)		0.62
B. May 1986-1998								
	(5)	0.0000 (.03)	-0.821 (-11.16)	0.413 (2.47)	-0.005 (-2.22)	0.376 (3.74)		0.68
	(6)	0.0001 (.53)					0.011 (2.89)	0.05
	(7)	0.0000 (.02)	-0.831 (-11.52)	0.326 (1.95)	-0.005 (-2.12)	0.372 (3.77)	0.006 (2.66)	0.69

Table 7. Regressions Using Alternate Measures of Risk Premia to Analyze Potential Effects of Reporting Lags in Analysts' Forecasts

The table reports regression coefficients (*t*-values). Regression estimates use all variables expressed as changes (monthly or quarterly) to correct for autocorreclation. BSPREAD is the spread between yields on long-term corporate and government bonds. *rp* is the risk premium on the SP500 index. The yield to maturity on long-term government bonds is denoted as *i*. For purposes of the regression, variables are expressed in decimal form, e.g., 12% = .12.

Dependent Variable	Intercept	*i*	BSPREAD	*Adj.* R^2
(1) Equity Risk Premium (*rp*) Monthly Observations (same as Table 5)	-.0002 (-1.11)	-.749 (-11.37)	.487 (2.94)	.59
(2) Equity Risk Premium (*rp*) "Quarterly" nonoverlapping observations to account for lags in analyst reporting	-.0002 (-.49)	-.527 (-6.18)	.550 (2.20)	.60
(3) Corporate Bond Spread (BSPREAD) Monthly Observations	-.0001 (-1.90)	-.247 (-11.29)		.38

REFERENCES

R.B. Boebel, "The Information Content of Financial Analysts' Forecasts: Short-term vs. Long-term," University of North Carolina at Chapel Hill, Dissertation, 1991. University Microfilms International order number 9207936.

R.B. Boebel, M.N. Gultekin and R.S. Harris, "Financial Analysts' Forecast of Corporate Earnings Growth: Top Down Versus Bottom Up," in *Handbook of Security Analyst Forecasting and Asset Allocation*, John B. Guerard, Jr. and Mustafa N. Gultekin (eds.), London, JAI Press, 1993, pp. 185-192.

D. Brigham, D. Shome, and S. Vinson, "The Risk Premium Approach to Measuring A Utility's Cost of Equity," *Financial Management* (Spring 1985), pp. 33-45.

L.D. Brown, " Earnings Forecasting Research: Its Implications for Capital Market Research," *International Journal of Forecasting* (November 1993), pp. 295-320.

L.D. Brown, "Analyst Forecasting Errors: Additional Evidence," *Financial Analysts Journal* (November/December 1997), pp. 81-90.

R.F. Bruner, K. Eades, R. Harris and R. Higgins, Best Practices in Estimating the Cost of Capital: Survey and Synthesis," *Financial Practice and Education* (Spring/Summer 1998), pp. 13-28.

W.T. Carleton and J. Lakonishok, "Risk and Return on Equity: The Use and Misuse of Historical Estimates," *Financial Analysts Journal* (January/February 1985), pp. 38-47.

L. Chan, Y. Hamao, and J. Lakonishok, "Fundamental and Stock Returns in Japan," *Journal of Finance*, 46, (5), (December 1991) pp. 1739-64.

J. Cragg and B.G. Malkiel, *Expectations and the Structure of Share Prices*, National Bureau of Economic Research, Chicago, University of Chicago Press, 1982.

Goldman Sachs, *EVA Company Analysis*, January 1999.

R.S. Harris, "Using Analysts' Growth Forecasts to Estimate Shareholder Required Rates of Return," *Financial Management* (Spring 1988), pp. 58-67.

Ibbotson Associates, Inc., *1998 Cost of Capital Quarterly*, 1998 Yearbook

Ibbotson Associates, Inc., *1997 Stocks, Bonds, Bills, and Inflation*, 1997 Yearbook.

J. Johnston, *Econometric Methods*, New York, McGraw-Hill, 3rd edition, 1984.

P. Kennedy, *A Guide to Econometrics*, Cambridge, MIT Press, 2nd edition, 1985.
G.S. Madalla, *Econometrics*, New York, McGraw-Hill, 1977.

B. Malkiel, "Risk and Return: A New Look," in *The Changing Role of Debt and Equity in Financing U.S. Capital Formation*, B.B. Friedman (ed.), National Bureau of Economic Research, Chicago, University of Chicago Press, 1982.

B. Malkiel, "The Capital Formation Problem in the United States," *Journal of Finance* (May 1979), pp. 291-306.

F. Marston, R. Harris, and P. Crawford, "Risk and Return in Equity Markets: Evidence Using Financial Analysts' Forecasts," in *Handbook of Security Analysts' Forecasting and Asset Allocation*, J. Guerard and M. Gultekin (eds.), Greenwich, CT, JAI Press, 1992, pp. 101-122.

F. Marston and R.S. Harris, "Risk, Return, and Equilibrium: A Revisit Using Expected Returns," *Financial Review*, (February 1993).

J. Siegel and R. Thaler, "Anomalies: The Equity Premium Puzzle," *Journal of Economic Perspectives*, 11 (1), (1997), pp. 191-200.

J. VanderWeide and W.T. Carleton, "Investor Growth Expectations: Analysts vs. History," *Journal of Portfolio Management* (Spring 1988), pp. 78-82.

I. Welch, "Views of Financial Economists on the Equity Premium and Other Issues," UCLA/Anderson Finance Working Paper 10-98, May 18, 1998.

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Estimating Shareholder Risk Premia Using Analysts' Growth Forecasts

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■ One of the most widely used concepts in finance is that shareholders require a risk premium over bond yields to bear the additional risks of equity investments. While models such as the two-parameter capital asset pricing model (CAPM) or arbitrage pricing theory offer explicit methods for varying risk premia across securities, the models are invariably linked to some underlying market (or factor-specific) risk premium. Unfortunately, the theoretical models provide limited practical advice on establishing empirical estimates of such a benchmark market risk premium. As a result, the typical advice to practitioners is to estimate the market risk premium based on historical realizations of share and bond returns (see Brealey and Myers [3]).

In this paper, we present estimates of shareholder required rates of return and risk premia which are derived using forward-looking analysts' growth forecasts. We update, through 1991, earlier work which, due to data availability, was restricted to the period 1982-1984 (Harris [12]). Using stronger tests, we also reexamine the efficacy of using such an expectational approach as an alternative to the use of historical averages. Using the S&P 500 as a proxy for the market portfolio, we find an average market risk premium (1982-1991) of 6.47% above yields on long-term U.S. government bonds and 5.13% above yields on corporate bonds. We also find that required returns for individual stocks vary directly with their risk (as proxied by beta) and that the market risk premium varies over time. In particular, the equity market premium over government bond yields is higher in low interest rate environments and when there is a larger spread between corporate and government bond yields. These findings show that, in addition to fitting the theoretical requirement of being forward-looking, the utilization of analysts' forecasts in estimating return requirements provides reasonable empirical results that can be useful in practical applications.

Section I provides background on the estimation of equity required returns and a brief discussion of related

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literature on financial analysts' forecasts (FAF). In Section II, models and data are discussed. Following a comparison of the results to historical risk premia, the estimates are subjected to economic tests of both their time-series and cross-sectional characteristics in Section III. Finally, conclusions are offered in Section IV.

I. Background and Literature Review

In establishing economic criteria for resource allocation, it is often convenient to use the notion of a shareholder's required rate of return. Such a rate (k) is the minimum level of expected return necessary to compensate the investor for bearing risks and receiving dollars in the future rather than in the present. In general, k will depend on returns available on alternative investments (e.g., bonds or other equities) and the riskiness of the stock. To isolate the effects of risk, it is useful to work in terms of a risk premium (rp), defined as

$$rp = k - i, \tag{1}$$

where i = required return for a zero risk investment.[1]

Lacking a superior alternative, investigators often use averages of historical realizations to estimate a benchmark "market" risk premium which then may be adjusted for the relative risk of individual stocks (e.g., using the CAPM or a variant). The historical studies of Ibbotson Associates [13] have been used frequently to implement this approach.[2] This historical approach requires the assumptions that past realizations are a good surrogate for future expectations and, as typically applied, that risk premia are constant over time. Carleton and Lakonishok [5] demonstrate empirically some of the problems with such historical premia when they are disaggregated for different time periods or groups of firms.

As an alternative to historical estimates, the current paper derives estimates of k, and hence, implied values of rp, using publicly available expectational data. This expectational approach employs the dividend growth model (hereafter referred to as the discounted cash flow or DCF model) in which a consensus measure of financial analysts' forecasts (FAF) of earnings is used as a proxy for investor expectations. Earlier works by Malkiel [17], Brigham, Vinson, and Shome [4], and Harris [12] have used FAF in DCF models, and this approach has been employed in regulatory settings (see Harris [12]) and suggested by consultants as an alternative to use of historical data (e.g., Ibbotson Associates [13, pp. 127, 128]). Unfortunately, the published studies use data extending to 1984 at the latest. Our paper draws on this earlier work but extends it through 1991.[3] Our work is closest to that done by Harris [12], who reviews literature showing a strong link between equity prices and FAF and supporting the use of FAF as a proxy for investor expectations. Using data from 1982 to 1984, Harris' results suggest that this expectational approach to estimating equity risk premia is an encouraging alternative to the use of historical averages. He also demonstrates that such risk premia vary both cross-sectionally with the riskiness of individual stocks and over time with financial market conditions.

II. Models and Data

A. Model for Estimation

The simplest and most commonly used version of the DCF model to estimate shareholders' required rate of return, k, is shown in Equation (2):

$$k = \left(\frac{D_1}{P_0}\right) + g, \tag{2}$$

where D_1 = dividend per share expected to be received at time one, P_0 = current price per share (time 0), and g = expected growth rate in dividends per share. The limitations of this model are well known, and it is straightforward to derive expressions for k based on more general specifications of the DCF model.[4] The primary difficulty in using the DCF model is obtaining an estimate of g, since it should reflect market expectations of future perfor-

[1]Theoretically, i is a risk-free rate, though empirically its proxy (e.g., yield to maturity on a government bond) is only a "least risk" alternative that is itself subject to risk. In this development, the effects of tax codes on required returns are ignored.

[2]Many leading texts in financial management use such historical risk premia to estimate a market return. See, for example, Brealey and Myers [3]. Often a market risk premium is adjusted for the observed relative risk of a stock.

[3]See Harris [12] for a discussion of the earlier work and a detailed discussion of the approach employed here.

[4]As stated, Equation (2) requires expectations of either an infinite horizon of dividend growth at a rate g or a finite horizon of dividend growth at rate g and special assumptions about the price of the stock at the end of that horizon. Essentially, the assumption must ensure that the stock price grows at a compound rate of g over the finite horizon. One could alternatively estimate a nonconstant growth model, although the proxies for multistage growth rates are even more difficult to obtain than single stage growth estimates. Marston, Harris, and Crawford [19] examine publicly available data from 1982-1985 and find that plausible measures of risk are more closely related to expected returns derived from a constant growth model than to those derived from multistage growth models. These findings illustrate empirical difficulties in finding empirical proxies for multistage growth models for large samples.

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mance. Without a ready source for measuring such expectations, application of the DCF model is fraught with difficulties. This paper uses published FAF of long-run growth in earnings as a proxy for g.

B. Data

FAF for this research come from IBES (Institutional Broker's Estimate System), which is a product of Lynch, Jones, and Ryan, a major brokerage firm.[5] Representative of industry practice, IBES contains estimates of (*i*) EPS for the upcoming fiscal years (up to five separate years), and (*ii*) a five-year growth rate in EPS. Each item is available at monthly intervals.

The mean value of individual analysts' forecasts of five-year growth rate in EPS will be used as a proxy for g in the DCF model.[6] The five-year horizon is the longest horizon over which such forecasts are available from IBES and often is the longest horizon used by analysts. IBES requests "normalized" five-year growth rates from analysts in order to remove short-term distortions that might stem from using an unusually high or low earnings year as a base.

Dividend and other firm-specific information come from COMPUSTAT. Interest rates (both government and corporate) are gathered from Federal Reserve Bulletins and *Moody's Bond Record*. Exhibit 1 describes key variables used in the study. Data collected cover all dividend paying stocks in the Standard & Poor's 500 stock (S&P 500) index, plus approximately 100 additional stocks of regulated companies. Since five-year growth rates are first available from IBES beginning in 1982, the analysis covers the 113-month period from January 1982 to May 1991.

III. Risk Premia and Required Rates of Return

A. Construction of Risk Premia

For each month, a "market" required rate of return is calculated using each dividend paying stock in the S&P 500 index for which data are available. The DCF model in Equation (2) is applied to each stock and the results weighted by market value of equity to produce the market required return.[7] The return is converted to a risk premium

Exhibit 1. Variable Definitions

k	=	Equity required rate of return.
P_0	=	Average daily price per share.
D_1	=	Expected dividend per share measured as current indicated annual dividend from COMPUSTAT multiplied by $(1 + g)$.[a]
g	=	Average financial analysts' forecast of five-year growth rate in earnings per share (from IBES).
i_g	=	Yield to maturity on long-term U.S. government obligations (source: Federal Reserve Bulletin, constant maturity series).
i_c	=	Yield to maturity on long-term corporate bonds: Moody's average.[b]
rp	=	Equity risk premium calculated as $rp = k - i$.
β	=	beta, calculated from CRSP monthly data over 60 months.

Notes:

[a]See footnote 7 for a discussion of the $(1 + g)$ adjustment.

[b]The average corporate bond yield across bond rating categories as reported by Moody's. See *Moody's Bond Survey* for a brief description and the latest published list of bonds included in the bond rating categories.

[5]Harris [12] provides a discussion of IBES data and its limitations. In more recent years, IBES has begun collecting forecasts for each of the next five years. Since this work was completed, the FAF used here have become available from IBES Inc., now a subsidiary of CitiBank.

[6]While the model calls for expected growth in dividends, no source of data on such projections is readily available. In addition, in the long run, dividend growth is sustainable only via growth in earnings. As long as payout ratios are not expected to change, the two growth rates will be the same.

[7]The construction of D_1 is controversial since dividends are paid quarterly and may be expected to change during the year; whereas, Equation (2), as is typical, is being applied to annual data. Both the quarterly payment of dividends (due to investors' reinvestment income before year's end, see Linke and Zumwalt [15]) and any growth during the year require an upward adjustment of the current annual rate of dividends to construct D_1. If quarterly dividends grow at a constant rate, both factors could be accommodated straightforwardly by applying Equation (2) to quarterly data with a quarterly growth rate and then annualizing the estimated quarterly required return. Unfortunately, with lumpy changes in dividends, the precise nature of the adjustment depends on both an individual company's pattern of growth during the calendar year and an individual company's required return (and hence reinvestment income in the risk class).

In this work, D_1 is calculated as $D_0(1 + g)$. The full g adjustment is a crude approximation to adjust for both growth and reinvestment income. For example, if one expected dividends to have been raised, on average, six months ago, a "1/2 g" adjustment would allow for growth, and the remaining "1/2 g" would be justified on the basis of reinvestment income. Any precise accounting for both reinvestment income and growth would require tracking each company's dividend change history and making explicit judgments about the quarter of the next change. Since no organized "market" forecast of such a detailed nature exists, such a procedure is not possible. To get a feel for the magnitudes involved, during the sample period the dividend yield (D_1/P_0) and growth (market value weighted) for the S&P 500 were typically 4% to 6% and 11% to 13%, respectively. As a result, a "full g" adjustment on average increases the required return by 60 to 70 basis points (relative to no g adjustment).

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Exhibit 2. Bond Market Yields, Equity Required Return, and Equity Risk Premium.[a] 1982-1991

	Bond Market Yields[b]		Equity Market Required Return[c]	Equity Risk Premium	
Year	(1) U.S. Gov't	(2) Moody's Corporates	(3) S&P 500	U.S. Gov't (3)-(1)	Moody's Corporates (3)-(2)
1982	12.92	14.94	20.08	7.16	5.14
1983	11.34	12.78	17.89	6.55	5.11
1984	12.48	13.49	17.26	4.78	3.77
1985	10.97	12.05	16.32	5.37	4.28
1986	7.85	9.71	15.09	7.24	5.38
1987	8.58	9.84	14.71	6.13	4.86
1988	8.96	10.18	15.37	6.41	5.19
1989	8.46	9.66	15.06	6.60	5.40
1990	8.61	9.77	15.69	7.08	5.92
1991[d]	8.21	9.41	15.61	7.40	6.20
Average[e]	9.84	11.18	16.31	6.47	5.13

Notes:

[a]Values are averages of monthly figures in percent.

[b]Yields to maturity.

[c]Required return on value weighted S&P 500 index using Equation (1).

[d]Figures for 1991 are through May.

[e]Months weighted equally.

over government bonds by subtracting i_{g}, the yield to maturity on long-term government bonds. A risk premium over corporate bond yields is also constructed by subtracting i_c, the yield on long-term corporate bonds. Exhibit 2 reports the results by year (averages of monthly data).

The results are quite consistent with the patterns reported earlier (i.e., Harris [12]). The estimated risk premia in Exhibit 2 are positive, consistent with equity owners demanding additional rewards over and above returns on debt securities. The average expectational risk premium (1982 to 1991) over government bonds is 6.47%, only slightly higher than the 6.16% average for 1982 to 1984 reported earlier (Harris [12]). Furthermore, Exhibit 2 shows the estimated risk premia change over time, suggesting changes in the market's perception of the incremental risk of investing in equity rather than debt securities.

For comparison purposes, Exhibit 3 contains historical returns and risk premia. The average expectational risk premium reported in Exhibit 2 falls roughly midway between the arithmetic (7.5%) and geometric (5.7%) long-term differentials between returns on stocks and long-term government bonds. Note, however, that the expectational risk premia appear to change over time. In the following sections, we examine the estimated risk premia to see if they vary cross-sectionally with the risk of individual stocks and over time with financial market conditions.

B. Cross-Sectional Tests

Earlier, Harris [12] conducted crude tests of whether expectational equity risk premia varied with risk proxied by bond ratings and the dispersion of analysts' forecasts and found that required returns increased with higher risk. Here we examine the link between these premia and beta, perhaps the most commonly used measure of risk for equities.[8] In keeping with traditional work in this area, we adopt the methodology introduced by Fama and Macbeth [9] but replace realized returns with expected returns from Equation (2) as the variable to be explained. For this portion of our tests, we restrict our sample to 1982-1987

[8]For other efforts using expectational data in the context of the two-parameter CAPM, see Friend, Westerfield, and Granito [10], Cragg and Malkiel [7], Marston, Crawford, and Harris [19], Marston and Harris [20], and Linke, Kannan, Whitford, and Zumwalt [16]. For a more complete treatment of the subject, see Marston and Harris [20] from which we draw some of these results. Marston and Harris also investigate the role of unsystematic risk and the difference in estimates found when using expected versus realized returns.

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Exhibit 3. Average Historical Returns on Bonds, Stocks, Bills, and Inflation in the U.S., 1926-1989

Historical Return Realizations	Geometric	Arithmetic
Common stock	10.3%	12.4%
Long-term government bonds	4.6%	4.9%
Long-term corporate bonds	5.2%	5.5%
Treasury bills	3.6%	3.7%
Inflation rate	3.1%	3.2%

Source: Ibbotson Associates, Inc., *1990 Stocks, Bonds, Bills and Inflation*, 1990 Yearbook.

and in any month include firms that have at least three forecasts of earnings growth to reduce measurement error associated with individual forecasts.[9] This restricted sample still consists of, on average, 399 firms for each of the 72 months (or 28,744 company months).

For a given company in a given month, beta is estimated via the market model (using ordinary least squares) on the prior 60 months of return data taken from CRSP. Beta estimates are updated monthly and are calculated against an equally weighted index of all NYSE securities. For each month, we aggregate firms into 20 portfolios (consisting of approximately 20 securities each). The advantage of grouped data is the reduction in potential measurement error inherent in independent variables at the company level. Portfolios are formed based on a ranking of beta estimated from a prior time period (t = -61 to t = -120). Portfolio expected returns and beta are calculated as the simple averages for the individual securities.

Using these data, we estimate the following model for each of the 72 months:

$$R_p = \alpha_0 + \alpha_1 \beta_p + u_p, \quad p = 1...20, \qquad (3)$$

where:

- R_p = Expected return for portfolio p in the given month,
- β_p = Portfolio beta, estimated over 60 prior months, and
- u_p = A random error term with mean zero.

As a result of estimating regression (3) for each month, 72 estimates of each coefficient (α_0 and α_1) are obtained. Using realized returns as the dependent variable, the traditional approach (e.g., Fama and Macbeth [9]) is to assume that realized returns are a fair game. Given this assumption, the mean of the 72 values of each coefficient is an unbiased estimate of the mean over that same time period if one could have actually used expected returns as the dependent variable. Note that if expected returns are used as the dependent variable the fair-game assumption is not required. Making the additional assumption that the true value of the coefficient is constant over the 72 months, a test of whether the mean coefficient is different from zero is performed using a t-statistic where the denominator is the standard error of the 72 values of the coefficient. This is the technique employed by Fama and Macbeth [9]. If one assumes the CAPM is correct, the coefficient α_1 is an empirical estimate of the market risk premium, which should be positive.

To test the sensitivity of the results, we also repeat our procedures using individual security returns rather than portfolios. To account, at least in part, for differences in precision of coefficient estimates in different months we also report results in which monthly parameter estimates are weighted inversely by the standard error of the coefficient estimate rather than being weighted equally (following Chan, Hamao, and Lakonishok [6]).

Exhibit 4 shows that there is a significant positive link between expectational required returns and beta. For instance, in Panel A, the mean coefficient of 2.78 on beta is significantly different from zero at better than the 0.001 level (t = 35.31), and each of the 72 monthly coefficients going into this average is positive (as shown by that 100% positive figure). Using individual stock returns, the significant positive link between beta and expected return remains, though it is smaller in magnitude than for portfolios.[10] Comparison of Panels A and B shows that the results are not sensitive to the weighting of monthly coefficients.

While the findings in Exhibit 4 suggest a strong positive link between beta and risk premia (a result often not supported when realized returns are used as a proxy for expectations; e.g., see Tinic and West [22]), the results do not support the predictions of a simple CAPM. In particular, the intercept is higher than a proxy for the risk-free rate over the sample period and the coefficient of beta is well below estimates of a market risk premium obtained from either expectational (Exhibit 2) or historical data (Exhibit

[9]Firms for which the standard deviation of individual FAF exceeded 20 in any month were excluded since we suspect some of these involve errors in data entry. This screen eliminated very few companies in any month. The 1982-1987 period was chosen due to the availability of data on betas.

[10]The smaller coefficients on beta using individual stock portfolio returns are likely due in part to the higher measurement error in measuring individual stock versus portfolio betas.

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Exhibit 4. Mean Values of Monthly Parameter Estimates for the Relationship Between Required Returns and Beta for Both Portfolios and Individual Securities (Figures in Parentheses are *t* Values and Percent Positive), 1982-1987

	Intercept	B	Adjusted R^2 [c]	F[c]
Panel A. Equal Weighting[a]				
Portfolio returns	14.06 (54.02, 100)	2.78 (35.31, 100)	0.503	25.4
Security returns	14.77 (58.10, 100)	1.91 (16.50, 99)	0.080	39.0
Panel B. Weighted by Standard Errors[b]				
Portfolio returns	13.86 (215.6, 100)	2.67 (35.80, 100)	0.503	25.4
Security returns	14.63 (398.9, 100)	1.92 (47.3, 99)	0.080	39.0

[a]Equally weighted average of monthly parameters estimated using cross-sectional data for each of the 72 months, January 1982 - December 1987.
[b]In obtaining the reported means, estimates of the monthly intercept and slope coefficients are weighted inversely by the standard error of the estimate from the cross-sectional regression for that month.
[c]Values are averages for the 72 monthly regressions.

3).[11] Nonetheless, the results show that the estimated risk premia conform to the general theoretical relationship between risk and required return that is expected when investors are risk-averse.

C. Time Series Tests — Changes in Market Risk Premia

A potential benefit of using ex ante risk premia is the estimation of changes in market risk premia over time. With changes in the economy and financial markets, equity investments may be perceived to change in risk. For instance, investor sentiment about future business conditions likely affects attitudes about the riskiness of equity investments compared to investments in the bond markets. Moreover, since bonds are risky investments themselves, equity risk premia (relative to bonds) could change due to changes in perceived riskiness of bonds, even if equities displayed no shifts in risk. For example, during the high interest rate period of the early 1980s, the high level of interest rate volatility made fixed income investments more risky holdings than they were in a world of relatively stable rates.

Studying changes in risk premia for utility stocks, Brigham, et al [4] conclude that, prior to 1980, utility risk premia increased with the level of interest rates, but that this pattern reversed thereafter, resulting in an inverse correlation between risk premia and interest rates. Studying risk premia for both utilities and the equity market generally, Harris [12] also reports that risk premia appear to change over time. Specifically, he finds that equity risk premia decreased with the level of government interest rates, increased with the increases in the spread between corporate and government bond yields, and increased with increases in the dispersion of analysts' forecasts. Harris' study is, however, restricted to the 36-month period, 1982 to 1984.

Exhibit 5 reports results of analyzing the relationship between equity risk premia, interest rates, and yield spreads between corporate and government bonds. Following Harris [12], these bond yield spreads are used as a time series proxy for equity risk. As the perceived riskiness of corporate activity increases, the difference between yields on corporate bonds and government bonds should increase. One would expect the sources of increased riskiness to corporate bonds to also increase risks to shareholders. All regressions in Exhibit 5 are corrected for serial correlation.[12]

[11]Estimation difficulties confound precise interpretation of the intercept as the risk-free rate and the coefficient on beta as the market risk premium (see Miller and Scholes [21], and Black, Jensen, and Scholes [2]). The higher than expected intercept and lower than expected slope coefficient on beta are consistent with the prior studies of Black, Jensen, and Scholes [2], and Fama and MacBeth [9] using historical returns. Such results are consistent with Black's [1] zero beta model, although alternative explanations for these findings exist as well (as noted by Black, Jensen, and Scholes [2]).

[12]Ordinary least squares regressions showed severe positive autocorrelation in many cases, with Durbin Watson statistics typically below one. Estimation used the Prais Winsten method. See Johnston [14, pp. 321-325].

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Exhibit 5. Changes in Equity Risk Premia Over Time — Entries are Coefficient (t-value); Dependent Variable is Equity Risk Premium

Time period	Intercept	i_B	$i_c - i_B$	R^2
A. May 1991 1992	0.131	-0.651		0.53
	(19.82)	(-11.16)		
	0.092	-0.363	0.666	0.54
	(14.26)	(-6.74)	(5.48)	
B. 1982-1984	0.140	-0.637		0.43
	(8.15)	(-5.00)		
	0.064	-0.203	1.549	0.60
	(3.25)	(-1.63)	(4.84)	
C. 1985-1987	0.131	-0.739		0.74
	(7.73)	(-9.67)		
	0.110	-0.561	0.317	0.77
	(12.53)	(-7.30)	(1.87)	
D. 1988-1991	0.136	-0.793		0.68
	(16.23)	(-8.29)		
	0.130	-0.738	0.098	0.68
	(8.71)	(-4.96)	(0.40)	

Note: All variables are defined in Exhibit 1. Regressions were estimated using monthly data and were corrected for serial correlation using the Prais-Winsten method. For purposes of this regression, variables are expressed in decimal form, e.g., 14% = 0.14.

For the entire sample period, Panel A shows that risk premia are negatively related to the level of interest rates — as proxied by yields on government bonds, i_B. This negative relationship is also true for each of the subperiods displayed in Panels B through D. Such a negative relationship may result from increases in the perceived riskiness of investment in government debt at high levels of interest rates. A direct measure of uncertainty about investments in government bonds would be necessary to test this hypothesis directly.

For the entire 1982 to 1991 period, the addition of the yield spread risk proxy to the regressions dramatically lowers the magnitude of the coefficient on government bond yields, as can be seen by comparing Equations 1 and 2 of Panel A. Furthermore, the coefficient of the yield spread (0.666) is itself significantly positive. This pattern suggests that a reduction in the risk differential between investment in government bonds and in corporate activity is translated into a lower equity market risk premium. Further examination of Panels B through D, however, suggests that the yield spread variable is much more important in explaining changes in equity risk premia in the early portion of the 1980s than in the 1988 to 1991 period.

In summary, market equity risk premia change over time and appear inversely related to the level of government interest rates but positively related to the bond yield spread, which proxies for the incremental risk of investing in equities as opposed to government bonds.

IV. Conclusions

Shareholder required rates of return and risk premia are based on theories about investors' expectations for the future. In practice, however, risk premia are often estimated using averages of historical returns. This paper applies an alternate approach to estimating risk premia that employs publicly available expectational data. At least for the decade studied (1982 to 1991), the resultant average market equity risk premium over government bonds is comparable in magnitude to long-term differences (1926 to 1989) in historical returns between stocks and bonds. There is strong evidence, however, that market risk premia change over time and, as a result, use of a constant historical average risk premium is not likely to mirror changes in investor return requirements. The results also show that the expectational risk premia vary cross-sectionally with the relative risk (beta) of individual stocks.

The approach offers a straightforward and powerful aid in establishing required rates of return either for corporate investment decisions or in the regulatory arena. Since data are readily available on a wide range of equities, an investigator can analyze various proxy groups (e.g., portfolios of utility stocks) appropriate for a particular decision as well as analyze changes in equity return requirements over time.

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References

1. F. Black, "Capital Market Equilibrium with Restricted Borrowing," *Journal of Business* (July 1972), pp. 444-455.
2. F. Black, M. Jensen, and M. Scholes, "The Capital Asset Pricing Model: Some Empirical Results," in *Studies in the Theory of Capital Markets*, Michael Jensen (ed.), New York, Praeger, 1972.
3. R. Brealey and S. Myers, *Principles of Corporate Finance*, New York, McGraw-Hill, 4th edition, 1990.
4. E. Brigham, D. Shome, and S. Vinson, "The Risk Premium Approach to Measuring Utility's Cost of Equity," *Financial Management* (Spring 1985), pp. 33-45.
5. W.T. Carleton and J. Lakonishok, "Risk and Return on Equity: The Use and Misuse of Historical Estimates," *Financial Analysts Journal* (January/February 1985), pp. 38-47.
6. L. Chan, Y. Hamao, and J. Lakonishok, "Fundamental and Stock Returns in Japan," Working Paper, University of Illinois at Urbana-Champaign, July 1990.
7. J. Cragg and B.G. Malkiel, *Expectations and the Structure of Share Prices*, National Bureau of Economic Research, Chicago, University of Chicago Press, 1982.
8. E.J. Elton, M.J. Gruber, and M. Gultekin, "Expectations and Share Prices," *Management Science* (September 1981), pp. 975-987.
9. E. Fama and J. Macbeth, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy* (May 1973), pp. 607-636.
10. I. Friend, R. Westerfield, and M. Granito, "New Evidence on the Capital Asset Pricing Model," *Journal of Finance* (June 1978), pp. 903-917.
11. D. Givoly and J. Lakonishok, "Earnings Expectation and Properties of Earnings Forecasts —A Review and Analysis of the Research," *Journal of Accounting Literature* (Spring 1984), pp. 85-107.
12. R.S. Harris, "Using Analysts' Growth Forecasts to Estimate Shareholder Required Rates of Return," *Financial Management* (Spring 1988), pp. 58-67.
13. Ibbotson Associates, Inc., *1990 Stocks, Bonds, Bills, and Inflation*, 1990 Yearbook.
14. J. Johnston, *Econometric Methods*, New York, McGraw-Hill, 3rd edition, 1984.
15. C. Linke and J. Zumwalt, "Estimation Biases in Discounted Cash Flow Analyses of Equity Capital Cost in Rate Regulation," *Financial Management*, (Autumn 1984), pp. 15-21.
16. C. Linke, S. Kannan, D. Whitford, and J. Zumwalt, "Divergence of Opinion and Risk: An Empirical Analysis of Ex Ante Beliefs of Institutional Investors," Working Paper 1294, University of Illinois at Urbana-Champaign, October 1986.
17. B. Malkiel, "Risk and Return: A New Look," in *The Changing Role of Debt and Equity in Financing U.S. Capital Formation*, B.B. Friedman (ed.), National Bureau of Economic Research, Chicago, University of Chicago Press, 1982.
18. B. Malkiel, "The Capital Formation Problem in the United States," *Journal of Finance* (May 1979), pp. 291-306.
19. F. Marston, R. Harris, and P. Crawford, "Risk and Return in Equity Markets: Evidence Using Financial Analysts' Forecasts," in *Handbook of Security Analysts' Forecasting and Asset Allocation*, J. Guerard and M. Gultekin (eds.), Greenwich, CT, JAI Press, forthcoming.
20. F. Marston and R.S. Harris, "Risk, Return, and Equilibrium: A Revisit Using Expected Returns," University of Virginia Working Paper, September 1989.
21. M. Miller and M. Scholes, "Rates of Return in Relation to Risk: A Re-Examination of Some Recent Findings," in *Studies in the Theory of Capital Markets*, Michael Jensen (ed.), New York, Praeger, 1972.
22. S. Tinic and R. West, "Risk, Return, and Equilibrium: A Revisit," *Journal of Political Economy* (February 1986), pp. 126-147.
23. J. VanderWeide and W.T. Carleton, "Investor Growth Expectations: Analysts vs. History," *Journal of Portfolio Management* (Spring 1988), pp. 78-82.

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The Accuracy, Bias and Efficiency of Analysts' Long Run Earnings Growth Forecasts

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1. INTRODUCTION

Considerable research has now been undertaken into professional analysts' forecasts of companies' earnings in respect of both their accuracy relative to the predictions of time series models of earnings, and their rationality. The evaluation of the reliability of analysts' earnings growth forecasts is an important aspect of research in accounting and finance for a number of reasons. Firstly, many empirical studies employ analysts' consensus forecasts as a proxy for the market's expectation of future earnings in order to identify the unanticipated component of earnings. The use of consensus forecasts in this way is predicated on the assumption that they are unbiased and efficient forecasts of future earnings growth. Secondly, institutional investors make considerable use of analysts' forecasts when evaluating and selecting individual shares. The quality of the forecasts that they employ therefore has important practical consequences for portfolio performance. Finally, from an academic point of view, the performance of analysts' forecasts is interesting because it sheds light on the process by which agents form expectations about key economic and financial variables.

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Nearly all of the research to date, however, has been concerned with analysts' forecasts of quarterly and annual earnings per share.[1] While the properties of analysts' short run forecasts are undoubtedly important in their own right, it is long run expectations of earnings growth that are more relevant for security pricing (see, for instance, Brown et al., 1985). A number of papers have suggested that there is substantial mis-pricing in the stock market as a consequence of irrational long run earnings growth forecasts being incorporated into the market expectation of earnings growth (DeBondt, 1992; La Porta, 1996; Bulkley and Harris, 1997; and Dechow and Sloan, 1997). The evaluation of the performance of analysts' long run forecasts is clearly important as corroborating evidence.

This paper provides a detailed study of the accuracy, bias and efficiency of analysts' long run earnings growth forecasts for US companies. It identifies a number of characteristics of forecast earnings growth. Firstly, the accuracy of analysts' long run earnings growth forecasts is shown to be extremely low. So low, in fact, that they are inferior to the forecasts of a naïve model in which earnings are assumed to follow a martingale. Secondly, analysts' long run earnings growth forecasts are found to be significantly biased, with forecast earnings growth exceeding actual earnings growth by an average of about seven percent per annum. Thirdly, analysts' forecasts are shown to be weakly inefficient in the sense that forecast errors are correlated with the forecasts themselves. In particular, low forecasts are associated with low forecast errors, while high forecasts are associated with high forecast errors. The bias and inefficiency in analysts' long run forecasts are considerably more pronounced than in their short run and interim forecasts.

It is investigated whether analysts incorporate information about future earnings that is contained in current share prices. It is demonstrated that consistent with their short run and interim forecasts, analysts' long run earnings growth forecasts can be enhanced by assuming that each individual firm's earnings will evolve in such a way that its price-earnings ratio will converge to the current market average price-earnings ratio. Analysts therefore neglect valuable information about future earnings that is readily available at the time that their forecasts are made.

The source of analyst inaccuracy is explored by decomposing the mean square error of analysts' forecasts into two systematic components, representing the error that arises as a result of forecast bias and forecast inefficiency, and a random, unpredictable component. In principle, the systematic components of analysts' forecast errors can be eliminated by taking into account the bias and inefficiency in their forecasts. However, it is shown that the bias and inefficiency of analysts' forecasts contribute very little to their inaccuracy. Over eighty-eight percent of the mean square forecast error is random, while less than twelve percent is due to the systematic components. This is an important result for the users of analysts' forecasts since it means that correcting forecasts for their systematic errors can potentially yield only a small improvement in their accuracy.

A second decomposition is used to examine the level of aggregation at which forecast errors are made. The mean square forecast error is decomposed into the error in forecasting average earnings growth in the economy, the error in forecasting the deviation of average growth in each industry from average growth in the economy, and the error in forecasting the deviation of earnings growth for individual firms from average industry growth. It is demonstrated that the error in forecasting average earnings growth in the economy contributes relatively little to analysts' inaccuracy. Over half of total forecast error arises from the error in forecasting deviations of individual firm growth from average industry growth. The error in forecasting deviations of average industry growth from average growth in the economy is smaller, but also significant. However, there is evidence that this pattern is changing over time, with increasing accuracy at the industry level, and diminishing accuracy at the individual firm level.

Finally, it is shown that the performance of analysts' long run earnings growth forecasts varies substantially both with the characteristics of the company whose earnings are being forecast and of the forecast itself. The accuracy, bias and efficiency of analysts' forecasts is examined for sub-samples of firms partitioned by market capitalisation, price-earnings ratio, market-to-book ratio and the level of the forecast itself. The most reliable earnings growth forecasts are low forecasts issued for large companies with low price-earnings ratios and high market-to-book ratios. Again, this is of considerable practical importance since it offers users of analysts' forecasts some opportunity to discriminate between good and bad forecasts.

The organisation of this paper is as follows. The following section gives a detailed description of the data sources and the sample selection criteria. Section 3 describes the methodology used to evaluate forecast accuracy, bias and efficiency. Section 4 reports the results, while Section 5 concludes.

2. DATA

The sample is drawn from all companies listed on the New York, American and NASDAQ stock exchanges. Data on long run earnings growth expectations are taken from the Institutional Brokers Estimate System (IBES). The data item used in this paper is the 'expected EPS long run growth rate' (item 0), which has been reported by IBES since December 1981, and is defined as:

> the anticipated growth rate in earnings per share over the longer term. IBES Inc. requests that contributing firms focus on the five-year interval that begins on the first day of the current fiscal year and make their calculations based on projections of EPS before extraordinary items.

The expected long term growth rate is therefore taken to be the forecast average annual growth in earnings per share before extraordinary items, over the five year period that starts at the beginning of the current fiscal year.[2] The measure used in this paper is the median forecast calculated and reported in April of each year, t. The analysis was also conducted using the mean forecast, but the quantitative results are virtually identical, and the qualitative conclusions unchanged.[3]

Only December fiscal year end companies are included in the sample and so the use of the consensus forecast reported in April should ensure that the previous fiscal year's earnings are public information at the time that the individual forecasts that make up the consensus forecast are made (see Alford, Jones and Zmijewski, 1994). Restricting the sample to December fiscal year-end companies ensures that observations for a particular fiscal year span the same calendar period, thus allowing the identification of macroeconomic shocks that contemporaneously affect the earnings of all firms.

Actual growth in earnings is calculated using data on earnings per share, excluding extraordinary items, taken from the Standard and Poor's Compustat database (item EPSFX). Average annual earnings growth is computed as the average change in earnings over each five year period, from December of year $t-1$ to December of year $t+5$, scaled by earnings in December of year $t-1$. The need for five years' subsequent earnings growth data limits the sample period to the eleven years 1982–92. Data on a number of other variables are also used in the analysis. The share price and market capitalisation are both taken at the end of April of year t (Compustat items PRCCM and MKVALM). The market price-earnings ratio, used to test whether information contained in the share price is incorporated in analysts' forecasts, is computed as the price at the end of April in year t (item PRCCM) divided by earnings per share in the fiscal year ending December $t-1$ (item EPSFX). The market-to-book ratio is computed as the market value of the company in April of year t (item MKVALM) divided by the book value of the company in the fiscal year ending December of year $t-1$ (item CEQ).

There are a total of 7,660 firm-year observations that satisfy the data requirements for all the variables used in the analysis, and that have a December fiscal year-end. However, for 658 of these, earnings reported at the end of the preceding fiscal year are zero or negative. These are omitted from the sample since forecast growth has no natural interpretation when earnings in the base year are non-positive.[4] When initial earnings are close to zero, actual growth in earnings may take extreme values, resulting in outliers that have a disproportionately high degree of influence on the least squares regression results. There is no immediately obvious way to circumvent this problem without dropping some observations from the sample. The approach most commonly adopted is to omit observations for which the calculated growth rate, the forecast growth rate or the forecast error is above a certain threshold in absolute value, or for which calculated initial earnings are below a certain level. For instance, Fried and Givoly (1982) truncate observations for which forecast error exceeds 100%. Elton et al. (1984) include in their sample only those companies for which initial earnings are above 0.20 dollars per share. O'Brien (1988), in order to test the robustness of her results to outliers, also uses 0.20 dollars as a threshold value.

Capstaff et al. (1995) omit observations for which forecast earnings growth or forecast error exceeds 100%, while Capstaff et al. (1998) exclude companies for which forecast earnings growth or actual earnings growth exceeds 100%. In this paper, all observations for which actual earnings growth or forecast earnings growth exceeds 100% in absolute value are omitted from the analysis, reducing the sample by a further 336 firm-year observations. The final pooled sample comprises 6,666 firm-year observations.[5]

3. METHODOLOGY

(i) *Forecast Accuracy*

The metric used to evaluate forecast performance is the forecast error, defined as the difference between actual and forecast earnings growth:

$$fe_{it} = g_{it} - g_{it}^{f} \tag{1}$$

where fe_{it} is the forecast error for firm i corresponding to the forecast made at date t, g_{it} is actual earnings growth over the five year forecast period and g_{it}^{f} is forecast five year earnings growth. Forecast accuracy is evaluated using the mean square forecast error, which is computed in each year t as:

$$\text{MSFE}_t = \frac{1}{N}\sum_{i=1}^{N}(g_{it} - g_{it}^{f})^2. \tag{2}$$

The mean square forecast error for the pooled sample is computed over all firms and years. The mean square forecast error was chosen in preference to the mean absolute forecast error to maintain consistency with the subsequent analysis which uses the former measure rather than the latter. However, it should be noted that the use of the mean square forecast error is consistent with a quadratic loss function of risk averse economic agents (see Theil, 1964; and Mincer and Zarnovitz, 1969). It can be reported that the conclusions drawn about forecast accuracy are not sensitive to the choice of measure.

As a benchmark against which to compare the accuracy of analysts' long run forecasts, the performance of two 'naïve' forecasts is also considered. The first is the forecast generated by a martingale model of earnings, in which expected earnings growth is zero. The second is the forecast generated by a sub-martingale model, in which expected earnings is equal to a drift parameter that is identical for all firms. In each forecast year, the common drift parameter is set equal to the average growth rate in earnings over all firms, over the previous five year period.[6] This choice of naïve forecasts is motivated by the early evidence on the time series properties of earnings, which suggests that annual earnings follow a random walk, or a random walk with drift (see, for instance, Brooks and Buckmaster, 1976; or Foster, 1977). Although more recent evidence finds that annual earnings may have a mean reverting component (see Ramakrishnan and Thomas, 1992), the martingale and sub-martingale models of earnings nevertheless provide simple alternative models that are approximately consistent with the reported evidence.

(ii) Forecast Bias

In order for a forecast to be unbiased, the unconditional expectation of the forecast error must be zero. If the average forecast error is greater than zero then analysts are systematically over-pessimistic (since their forecasts are on average exceeded) while if the average forecast error is less than zero analysts are systematically over-optimistic (since their forecasts are on average unfulfilled). Unbiasedness is tested using the mean forecast error, which is computed in each year t as:

$$\mathrm{MFE}_t = \frac{1}{N}\sum_{i=1}^{N}(g_{it} - g_{it}^{f}). \tag{3}$$

The mean forecast error for the pooled sample is computed over all firms and years. The hypothesis that the mean forecast error is zero is tested using the standard error of the mean forecast error across all firms and years for the pooled sample, and across all firms for each of the annual samples.

(iii) Forecast Efficiency

A forecast is efficient if it optimally reflects currently available information, and is therefore associated with a forecast error that is unpredictable. If a forecast is strongly efficient, the forecast error is uncorrelated with the entire information set at time t. Strong efficiency is a stringent condition, and so more usually forecasts are instead tested for weak efficiency, which requires that the forecast error is uncorrelated with the forecast itself (see Nordhaus, 1987). Weak efficiency is tested by estimating the following regression:

$$g_{it} = \alpha + \beta g_{it}^{f} + v_{it}. \tag{4}$$

Under the null hypothesis that analysts' forecasts are weakly efficient, the intercept, α, should be zero, while the slope coefficient, β, should be unity. If β is significantly different from one then conditioning on the forecast itself, the forecast error is predictable.[7] If β is significantly less than one then analysts' forecasts are too extreme, in the sense that high forecasts are associated with high forecast errors, while low forecasts are associated with low forecast errors. If β is significantly greater than one then forecasts are too compressed.

(iv) The Incremental Information Content of Price-Earnings Based Forecasts

A stronger form of forecast efficiency can be tested by examining whether analysts' forecasts incorporate particular sources of publicly available information. One such source of information is the current share price. In an efficient market, the share price is the present discounted value of all rationally expected future economic earnings of the company, and hence it should reflect, *inter alia,* the market's expectation of long run earnings growth. To extract the information about future earnings embodied in the share price, some assumption must be made about the company's cost of equity, or risk. The simplest assumption is that all companies face the same constant cost of equity in the long run, so that the earnings of each company evolve in such a way that its price-earnings ratio converges to the current market average price-earnings ratio. The earnings growth forecast that is implicit in this assumption can then be used to supplement the analysts' earnings growth forecast in the following regression:

$$g_{it} = \alpha + \beta g_{it}^{f} + \gamma g_{it}^{p} + v_{it}, \tag{5}$$

where

$$g_{it}^{p} = \frac{p_{it}/pe_{mt} - e_{it}}{e_{it}}, pe_{mt} = \frac{1}{N}\sum_{i=1}^{N}\frac{p_{it}}{e_{it}}$$

and p_{it} is the share price of firm i at time t. If analysts incorporate all information contained in the current share price, the coefficient, γ, should be zero (see Capstaff et al., 1995 and 1998). Naturally, the assumption that all firms have the same long run price-earnings ratio is a strong simplification, and a superior forecast would almost certainly be obtained by assuming that price-earnings ratios differ between industries. Nevertheless, the assumption of a single market-wide long run price-earnings ratio has been shown to forecast earnings growth over shorter horizons (see, for instance, Ou and Penman, 1989).

(v) Forecast Error Decomposition

In order to analyse the source of analysts' forecast errors, two decompositions of the mean square forecast error are used. The first decomposes the mean square forecast error into systematic and unsystematic components. The systematic component is further divided into a component due to forecast bias and a component due to forecast inefficiency. In each year t, the decomposition of the MSFE is given by:

$$\text{MSFE}_t = \frac{1}{N_t}\sum_{i=1}^{N_t}(g_{it}-g_{it}^{f})^2 = (\overline{g}_t-\overline{g}_t^{f})^2 + (1-\beta_t)^2\sigma^2_{g^f t} + (1-\rho_t^2)\sigma^2_{gt} \tag{6}$$

where N_t is the sample size in year t, $\overline{g}_t$ and $\overline{g}_t^{f}$ are the average values of g_{it} and g_{it}^{f}, β_t is the slope coefficient from regression (4), above, ρ_t is the correlation coefficient between g_{it} and g_{it}^{f}, and $\sigma^2_{g^f t}$ and σ^2_{gt} are the variances of g_{it} and g_{it}^{f}. The first term in the decomposition gives the error that is due to the inability of analysts to forecast earnings growth for the whole sample. When computed over all years, it is therefore a measure of the error that is due to forecast bias. The second term captures the error that is due to forecast inefficiency. Together, these two terms capture the systematic error in analysts' forecasts. In contrast, the third term captures the component of the error that is purely random. This decomposition is particularly useful since it reveals to what extent forecasts can be improved through 'optimal linear correction' procedures (see Mincer and Zarnovitz, 1969; and Theil, 1966). For instance, if the main component of mean square error is systematic, rather than random, then assuming that the data generating process for both the actual data and the forecast data remains constant, the accuracy of analysts' forecasts can be substantially improved by using the predicted values from regression (4), above, rather than the forecasts themselves. The extent to which this reduces the inaccuracy of the forecasts depends upon the fraction of the mean square forecast error that is due to the systematic component.

The second decomposition breaks the mean square forecast error into economy, industry and firm components. The decomposition of the MSFE is given each year t by:

$$
\begin{aligned}
\mathrm{MSFE}_t &= \frac{1}{N}\sum_{i=1}^{N_t}(g_{it} - g_{it}^f)^2 \\
&= (\overline{g}_t - \overline{g}_t^f)^2 + \frac{1}{N_t}\sum_{j=1}^{J_t} N_{jt}[(\overline{g}_{jt} - \overline{g}_t) - (\overline{g}_{jt}^f - \overline{g}_t^f)]^2 \qquad (7) \\
&\quad + \frac{1}{N_t}\sum_{i=1}^{Nt}[(g_{it} - \overline{g}_{jt}) - (g_{it}^f - \overline{g}_{jt}^f)]^2,
\end{aligned}
$$

where J_t is the number of industries in the sample, N_{jt} is the number of firms in industry j, $\overline{g}_{jt}$ and $\overline{g}_{jt}^f$ are the average values of g_{it} and g_{it}^f in industry j. The decomposition has the following interpretation. As before, the first term measures the error that is due to analysts' inability to forecast the average growth for the whole sample, which in this context may be interpreted as their inability to forecast earnings growth for the economy. The second term measures the error that is due to an inability to forecast the deviation of average growth in an industry from average growth in the economy. The third term measures the error that is due to an inability to forecast deviation of individual firm growth from average growth in its industry. The decomposition for the pooled sample is computed by taking the weighted average of the decomposition for the annual samples, with weights proportional to the sample size each year. Such a decomposition is useful because it reveals the level of aggregation at which forecast errors are made, and may reflect the particular approach used to generate earnings growth forecasts (see Elton, Gruber and Gultekin, 1984). In the present study, each industry is defined by a two digit SIC code. This yields a total of 56 industries, with an average of about twelve firms in each industry. The use of three digit SIC codes yields a large number of industries that comprise only a single firm. In these cases, the firm-specific error and industry specific error are not separately identifiable, and are reflected in the third component of the decomposition. The effect of using two digit, rather than three digit SIC codes is therefore to increase the firm specific error and reduce the industry specific error.

For both decompositions, it is convenient to express each term as a percentage of the total mean square forecast error. For the pooled samples, the mean square forecast error components are averaged over the individual years, with weights proportional to the sample size each year.

(vi) The Performance of Analysts' Forecasts Conditional on Firm and Forecast Characteristics

In order to explore possible heterogeneity in the performance of analysts' long run earnings growth forecasts, the sample is partitioned by various characteristics of the firm whose earnings are being forecast and of the forecast itself. Specifically, the sample is split into equally sized quintiles on the basis of market capitalisation, market-to-book ratio, price-earnings ratio and the level of the forecast itself. Forecast accuracy, bias and efficiency is then examined for each sub-sample. Forecast accuracy is measured by the mean square forecast error given by (2), forecast bias is measured by the mean forecast error given by (3), while forecast efficiency is measured by the estimated slope parameter in regression (4).

In order to identify the marginal effects of each of the firm and forecast characteristics on forecast accuracy, bias and weak form efficiency, the following regressions are estimated:

$$(g_{it} - g_{it}^f)^2 = \alpha + \beta_1 \ln m_{it} + \beta_2 mb_{it} + \beta_3 pe_{it} + \beta_4 g_{it}^f + v_{it}, \qquad (10)$$

$$g_{it} - g_{it}^f = \alpha + \beta_1 \ln m_{it} + \beta_2 mb_{it} + \beta_3 pe_{it} + \beta_4 g_{it}^f + v_{it} \qquad (11)$$

and

$$(g_{it}^f - \overline{g}_t^f)[(g_{it} - \overline{g}_t) - (g_{it}^f - \overline{g}_t^f)] = \alpha + \beta_1 \ln m_{it} + \beta_2 mb_{it} + \beta_3 pe_{it} + \beta_4 g_{it}^f + v_{it}, \quad (12)$$

where $\ln m_{it}$ is the natural logarithm of the market capitalisation of firm i at the beginning of the forecast period, mb_{it} is the market-to-book ratio and pe_{it} is the price-earnings ratio. The dependent variables in the three regressions are the summands in (a) the mean square forecast error, (b) the mean forecast error and (c) the estimated covariance between $(g_{it} - g_{it}^f)$ and g_{it}^f.[8]

(vii) Estimation Procedure

In order to allow for time specific market wide shocks, each of the regression equations (4), (5), (9), (10), (11) and (12) is estimated by OLS, including fixed time effects. However, inference based on OLS estimates of the variance-covariance matrix of the disturbance term may be misleading since both heteroscedasticity and cross-sectional correlation are likely to be present in the data. One potential solution is to use GLS, in which the heteroscedasticity and cross-section correlation are parameterised and estimated. However, in the present case, GLS is infeasible since the number of cross-section observations is large relative to the number of time series observations. This paper employs instead the non-parametric approach of Froot (1989), which is robust to both contemporaneous correlation and heteroscedasticity. This involves partitioning the data by a two digit SIC code and assuming that the intra-industry correlation is zero. This then allows the consistent estimation of the parameter covariance matrix. The Froot estimator is modified using the Newey-West (1987) procedure in order to allow for the serial correlation in the regression error term that is induced by the use of overlapping data.

4. RESULTS

(i) Forecast Accuracy

Panel A of Table 1 reports the mean square forecast error, given by (2), for the pooled sample and for each individual year. It also reports the mean square forecast errors for the naïve forecasts of the martingale model, where forecast earnings growth is zero, and the sub-martingale model, where forecast earnings growth is the historical economy wide average earnings growth rate.

The accuracy of analysts' long run earnings growth forecasts is extremely low. In the pooled sample, the mean square forecast error for analysts is 7.15%. For the martingale model, the mean square error is 6.63%, while for the sub-martingale model, it is marginally lower at 6.60%. On average, therefore, a superior forecast of long run earnings growth for individual companies can be obtained simply by assuming that average annual earnings growth will be zero. This is a strong indictment of the accuracy of analysts' long run forecasts, and in view of the additional information available to analysts, is surprising. It also contrasts with the evidence for shorter horizon forecasts where analysts appear to have some advantage over time series models. Furthermore, the alternative models used here are relatively simple. If in fact earnings are stationary, then it is likely that a yet superior forecast could be obtained from an estimated time series model for each firm, and so the relative inferiority of analysts' forecasts is probably understated here.

Turning to the annual samples, the martingale model generates superior forecasts in seven out of eleven years, while the sub-martingale model generates forecasts that are superior to analysts' forecast in nine of the eleven years, and superior to the forecasts of the martingale model in ten out of eleven years. This suggests that one can improve on the zero growth forecast of the martingale model by using the historical economy average earnings growth rate to predict subsequent growth for individual firms. However, the improvement is only marginal, reflecting both considerable variation in average earnings growth between years and considerable dispersion in earnings growth rates across the economy. The time-series pattern of forecast errors suggests that analyst inferiority is not caused by just one or two outlying years. Nor does it suggest that there is any improvement in the accuracy of analysts' forecasts over the sample period, either relative to the forecasts of the martingale and sub-martingale models, or in absolute terms. The (unweighted) average mean square forecast error for the first five years in the sample is 7.02%, while in the last five years it is 7.28%. This is in contrast with evidence reported elsewhere that analyst accuracy has increased over time (see Brown, 1997).

(ii) Forecast Bias

Panel B of Table 1 reports the mean forecast error for analysts' forecasts of long run earnings growth, given by (3), and its standard error. In the pooled sample, the mean forecast error is negative indicating that analysts' long run earnings growth forecasts are over-optimistic. The mean forecast error is very significant both in statistical and economic terms. On average, forecast growth exceeds actual growth by about seven percent per annum. Over-optimism in long run earnings growth forecasts is consistent with evidence reported for analysts' shorter horizon earnings forecasts (see, for instance, Fried and Givoly, 1982; Brown et al., 1985; and O'Brien, 1988). It is also consistent with international evidence on analysts short run and interim forecasts (see Capstaff et al., 1995 and 1998).

The mean forecast error is also negative in each individual year, and significantly negative in all but the last, ranging from 1.50% to 11.82% per annum. This is in contrast with analysts' shorter horizon forecasts where the direction of the reported bias displays considerable year to year variation (see, for instance, Givoly, 1985). It is again notable that the degree of over-optimism has not diminished significantly over time. The (unweighted) mean forecast error for the first five years of the sample is −6.99%, while for the last five years it is −7.20%. It is of course possible that the last year in the sample, where the mean forecast error is less than two percent, marks the start of a reduction in analyst over-optimism. Whether this is borne out by future studies will be of considerable interest.

(iii) Forecast Efficiency

Panel A of Table 2 presents the results of regression (4). The efficiency condition is very strongly rejected for analysts' long run earnings growth forecasts. In the pooled sample, $\hat{\beta}$ is significantly less than unity and at 0.20, only marginally greater than zero. This is a considerably stronger rejection of efficiency than found by other authors for shorter horizon forecasts. For instance,

Table 1

Forecast Accuracy and Forecast Bias

	Panel A: Forecast Accuracy			Panel B: Forecast Bias	
	MSFE of Analysts	*MSFE of Martingale*	*MSFE of Sub-martingale*	*MFE of Analysts*	*Standard Error*
Pooled sample	7.15	6.63	6.60	−7.33	(0.31)
1982	7.34	5.15	6.41	11.39	(1.01)
1983	6.88	7.01	6.51	5.48	(1.20)
1984	6.75	7.14	6.40	4.01	(1.12)
1985	7.19	6.67	6.29	−6.61	(1.08)
1986	6.92	6.47	6.24	−7.44	(1.08)
1987	6.95	5.77	5.75	10.78	(0.99)
1988	7.38	6.32	6.40	10.20	(1.00)
1989	6.99	5.22	5.71	−11.82	(0.91)
1990	5.69	5.20	4.95	−7.40	(0.85)
1991	7.58	7.78	7.60	5.04	(0.99)
1992	8.78	9.62	9.78	1.50	(1.10)

Notes:

Panel A reports the mean square forecast error for analysts' forecasts and the forecasts of two naïve models.

The MSFE of analysts forecasts is calculated each year as $\frac{1}{N}\sum_{i=1}^{N}(g_{it} - g_{it}^{f})^2$;

the MSFE of the martingale model is calculated each year as $\frac{1}{N}\sum_{i=1}^{N}(g_{it})^2$;

the MSFE of the sub-martingale model is calculated each year as $\frac{1}{N}\sum_{i=1}^{N}(g_{it} - \overline{g}_{t-1})^2$;

where g_{it} is five year earnings growth from January year t to December year $t+4$, is forecast of g_{it} reported at April year t and $\overline{g}_{t-1}$ is the average value over all companies of five year earnings growth from January year $t-5$ to December year $t-1$. The MSFE for the pooled sample is computed over all firms and years.

Panel B reports the mean forecast error of analysts, calculated as:

$$\text{MFE} = \frac{1}{N}\sum_{i=1}^{N}(g_{it} - g_{it}^{f}),$$

and its standard error. The MFE for the pooled sample is computed over all firms and years.

DeBondt and Thaler (1990) find that while they reject the hypothesis that β is equal to unity for one and two year forecasts, their estimated parameters (0.65 for one year forecasts, 0.46 for two year forecasts) are much larger than those reported here, both statistically and economically. For annual earnings forecasts,

Table 2

Forecast Efficiency

	Panel A: Weak Efficiency			Panel B: The Incremental Information Content of Price-Earnings Based Forecasts				
	$\hat{\beta}$	SE	$\overline{R}^2$	$\hat{\beta}$	SE	$\hat{\gamma}$	SE	$\overline{R}^2$
Pooled sample	0.20	(0.08)	0.00	0.05	(0.09)	0.04	(0.01)	0.02
1982	0.73	(0.26)	0.04	0.81	(0.28)	0.03	(0.04)	0.05
1983	0.42	(0.25)	0.01	0.08	(0.27)	0.05	(0.02)	0.04
1984	0.19	(0.27)	0.00	0.03	(0.30)	0.04	(0.02)	0.01
1985	0.05	(0.29)	0.00	0.02	(0.33)	0.01	(0.02)	0.00
1986	0.31	(0.23)	0.01	0.25	(0.22)	0.10	(0.02)	0.06
1987	0.46	(0.22)	0.01	0.41	(0.22)	0.01	(0.02)	0.01
1988	0.42	(0.21)	0.01	0.43	(0.21)	0.00	(0.01)	0.01
1989	0.08	(0.22)	0.00	−0.03	(0.23)	0.03	(0.02)	0.01
1990	0.28	(0.17)	0.01	0.20	(0.20)	0.02	(0.02)	0.01
1991	0.39	(0.17)	0.01	0.11	(0.50)	0.06	(0.03)	0.03
1992	0.09	(0.27)	0.00	−0.20	(0.31)	0.10	(0.03)	0.05

Notes:

Panel A reports the results of the test of the weak efficiency of analysts' forecasts. The regression for the pooled sample is $g_{it} = \alpha_t + \beta g^f_{it} + u_{it}$ where g_{it} is five year earnings growth from January year t to December year $t+4$ and g^f_{it} is the median forecast of g_{it} reported in April of year t. The regression for the annual samples is $g_{it} = \alpha_t + \beta_t g^f_{it} + u_{it}$. The Panel reports the estimated slope parameter, its Froot-Newey-West adjusted standard error and the adjusted R-squared statistic.

Panel B reports the results of the test for the incremental information content of price-earnings based forecasts. The regression for the pooled sample is $g_{it} = \alpha_t + \beta g^f_{it} + \gamma g^p_{it} + u_{it}$ where g_{it} is five year earnings growth from January year t to December year $t+4$, is the median forecast of g_{it} reported in April of year t,

$$g^p_{it} = \frac{p_{it}/pe_{mt} - e_{it}}{e_{it}}, \; pe_{mt} = \frac{1}{N}\sum_{i=1}^{N}\frac{p_{it}}{e_{it}},$$

e_{it} is the earnings reported in December of year $t-1$, and p_{it} is the price in April of year t. The regression for the annual samples is $g_{it} = \alpha_t + \beta_t g^f_{it} + \gamma_t g^p_{it} + u_{it}$. The Panel reports the estimated slope parameter, its Froot-Newey-West adjusted standard error and the adjusted R-squared statistic.

Givoly (1985) cannot reject the hypothesis that β is unity. Using UK data on the forecasts of individual analysts, Capstaff et al. (1995) find that the estimated coefficient declines with the forecast horizon, with an estimated value of around 0.5 for 20 month forecasts (their longest horizon). The results of this paper therefore strongly support the view (first offered by DeBondt and Thaler, 1990) that forecast earnings growth is too extreme, and that the longer the horizon, the more extreme it becomes. In the annual regressions, β is significantly less than unity in all years, and significantly greater than zero in only three years. In one year, it is actually significantly negative.

(iv) The Incremental Information Content of Price-Earnings Based Forecasts

The results of regression (5), which supplements analysts' forecasts with forecasts that are derived from the assumption that earnings will evolve in such a way that each firm's price-earnings ratio will converge to the current market price-earnings ratio, are reported in Panel B of Table 2. Under the null hypothesis that analysts make optimal use of information about future earnings that is contained in share prices, the coefficient on the price-earnings based forecast, $\hat{\gamma}$, should be zero. In the pooled sample, the estimated coefficient is significantly greater than zero, implying that analysts do not make full use of information that is readily available at the time that their forecasts are made. However, there is much year to year variation in both the statistical and economic significance of the coefficient, with six years in which the coefficient is not statistically different from zero.

The marginal contribution of price-earnings based forecasts can be gauged by comparing the two Panels of Table 2. The inclusion of the price-earnings forecast explains an additional two percent of the variation in actual earnings growth in the pooled sample, while in individual years, this figure varies between zero and five percent. However, the price-earnings based forecast used in the present analysis is derived under the somewhat unrealistic assumption that all firms have a common long run price-earnings ratio. Undoubtedly, more accurate earnings growth forecasts could be imputed by making more sophisticated assumptions about how price-earnings ratios evolve over time. The results presented here therefore almost certainly understate the extent to which analysts neglect information embodied in share prices. The fact that analysts appear to neglect information contained in share prices when forming their long run earnings growth forecasts is consistent with analogous results for their forecasts over shorter horizons (see, for instance, Ou and Penman, 1989; Abarbanell, 1991; Elgers and Murray, 1992; and Capstaff et al., 1995 and 1998).

(v) Forecast Error Decomposition

The preceding results demonstrate that the accuracy of analysts' long run earnings forecasts is extremely low, and that they are very significantly biased and inefficient. In this sub-section, the source of analysts' forecast error is investigated using the two decompositions of mean square forecast error described in Section 3. The first decomposes forecast error into systematic and non-systematic components. The results of this decomposition are given in Panel A of Table 3. It can be seen that by far the largest component of mean square forecast error is random. In the pooled sample, less than twelve percent of the forecast error is the result of the systematic component of analysts' forecast errors. Of the systematic component, about seven percent is due to bias, and about four percent due to inefficiency. A similar pattern holds for the annual samples, although there is considerable year to year variation, with as much as ninety-five percent of mean square forecast error accounted for by the random component in some years. In principle, knowledge of the systematic error in analysts' forecasts permits the use of 'optimal linear correction' techniques in order to improve forecast accuracy. This involves employing the predicted values calculated using the estimated coefficients from regression (4), above, in place of the forecasts themselves. The effect of the ordinary least squares regression is to adjust the forecasts by compensating for their bias and inefficiency. The degree to which accuracy can be enhanced in this way depends upon the proportion of the mean square forecast error that is systematic. The results reported here imply that, assuming that the underlying data generating process for actual earnings growth and the method by which analysts form the expectations of earnings growth remain constant, optimal linear correction of the forecasts will reduce the forecast error only by about twelve percent. This is clearly an important result for the users of analysts' forecasts.

The second decomposition divides the mean square forecast error into the error in forecasting average earnings growth in the economy, the error in forecasting the deviation of average growth in each industry from average growth in the economy, and the error in forecasting the deviation of earnings growth for

Table 3

Forecast Error Decomposition

	Panel A : Decomposition by Error Type			**Panel B: Decomposition by Level of Aggregation**		
	Bias	*Inefficiency*	*Random*	*Economy*	*Industry*	*Firm*
Pooled sample	7.51	4.07	88.45	9.21	35.53	55.25
1982	17.67	15.41	67.23	17.67	46.06	36.27
1983	4.37	2.12	93.92	4.37	40.21	55.42
1984	2.38	4.64	93.34	2.38	52.27	45.34
1985	6.07	6.68	87.57	6.07	36.45	57.48
1986	8.00	2.96	89.37	8.00	40.59	51.41
1987	16.73	1.86	81.69	16.73	30.15	53.11
1988	14.10	2.04	84.13	14.10	29.77	56.13
1989	20.02	5.32	74.89	20.02	27.45	52.53
1990	9.62	4.49	86.13	9.62	31.68	58.69
1991	3.35	2.63	94.27	3.35	33.05	63.60
1992	0.26	4.78	95.24	0.26	32.13	67.61

Notes:

Panel A reports the results of the decomposition of mean square forecast error for each year t by error type, given by:

$$\text{MSFE} = \frac{1}{N_t}\sum_{i=1}^{N_t}(g_{it}-g_{it}^f)^2 = (\overline{g}_t-\overline{g}_t^f)^2+(1-\beta_t)^2\sigma^2_{g^f t}+(1-\rho_t^2)\sigma^2_{gt}$$

where N_t is the sample size in year t, g_{it} is five year earnings growth from January year t to December year t+4, g_{it}^f is the median forecast of g_{it} reported in April of year t, $\overline{g}_t$ and $\overline{g}_t^f$ are the average values of g_{it} and g_{it}^f, β_t is the slope coefficient reported in Panel A of Table 2, ρ_t is the correlation coefficient between g_{it} and g_{it}^f, and σ^2_{gt} and $\sigma^2_{g^f t}$ are the variances of g_{it} and g_{it}^f. The decomposition for the pooled sample is computed over all firms and years.

Panel B reports the results of the decomposition of mean square forecast error for each year t by the level of aggregation, given by:

$$\text{MSFE} = \frac{1}{N_t}\sum_{i=1}^{N_t}(g_{it}-g_{it}^f)^2$$

$$= (\overline{g}_t-\overline{g}_t^f)^2+\frac{1}{N_t}\sum_{j=1}^{J_t}N_{jt}[(\overline{g}_{jt}-\overline{g}_t)-(\overline{g}_{jt}^f-\overline{g}_t^f)]^2+\frac{1}{N_t}\sum_{i=1}^{N_t}[(g_{it}-\overline{g}_{jt})-(g_{it}^f-\overline{g}_{jt}^f)]^2$$

where J_t is the number of industries in the sample, N_{jt} is the number of firms in industry j, $\overline{g}_{jt}$ and $\overline{g}_{jt}^f$ are the average values of g_{it} and g_{it}^f in industry j. The decomposition for the pooled sample is the weighted average of the decompositions for the annual samples, with weights proportional to the sample size each year. The table reports each of the components of mean square forecast error as a percentage of total mean square forecast error.

individual firms from average industry growth. The results of this decomposition are reported in Panel B of Table 3. The results demonstrate that analysts' forecast inaccuracy derives mainly from an inability to forecast deviations of individual firm growth from the average growth rate in its industry. The error in forecasting deviations of industry growth from the average growth rate in the economy is also important, but somewhat smaller than the error in forecasting individual firm growth. In contrast, analysts' inability to forecast average earnings growth in the economy contributes relatively little to their inaccuracy. An interesting feature of this decomposition is that the proportion of forecast error generated at the industry level appears to be diminishing over time, while the proportion generated at the individual firm level is increasing. This is potentially related to changes in the methods used by analysts to forecast earnings growth, or changes in accounting standards.

(vi) The Performance of Analysts' Forecasts Conditional on Firm and Forecast Characteristics

The foregoing analysis has considered analysts' long run earnings growth forecasts as a homogenous group. However, it is likely that forecast performance will vary with the characteristics of the firm whose earnings are being forecast. For instance, one would expect that firms with highly variable cash flows, or those for which little information is available about future earnings prospects, would be associated with lower forecast accuracy. Additionally, forecast performance is likely to vary with the size of the forecast itself since the efficiency results indicate that low forecasts are less overly-optimistic than high forecasts.

In order to investigate this issue, the accuracy, bias and efficiency results are reproduced for sub-samples of companies, partitioned on the basis of market capitalisation, price-earnings ratio, market-to-book ratio and the level of the forecast itself. For each variable, the sample is sorted into ascending order of the partitioning variable and split into quintiles, with equal numbers of firms in each quintile.[10] For all the results of this section, results are reported for quintiles pooled across all years only.

Table 4 presents the results for forecast accuracy, with the mean square forecast error for each quintile reported in Panel A.

There is substantial variation in forecast accuracy across market capitalisation, price-earnings ratio and forecast earnings growth, while there is no obvious systematic variation in forecast accuracy across market-to-book. Forecast accuracy increases with market capitalisation, with forecasts for the quintile of largest firms more than twice as accurate as those for the quintile of smallest firms. There is an inverse relationship between forecast accuracy and price-earnings ratio, with forecasts for the lowest quintile almost three times as accurate as those for the highest quintile. The largest variation in forecast accuracy is with the level of the forecast itself, with low forecasts being five times more accurate than high forecasts. In all three cases, variation in forecast accuracy is monotonic (almost monotonic in the case of price-earnings and forecast size), although it does not appear to be linear, with the largest differences occurring in the lowest and highest quintiles.

The results of Panel A show that forecast accuracy varies substantially with market capitalisation, price-earnings ratio and the forecast itself. However, these variables are not independent, and so variation in forecast accuracy with one variable may merely reflect variation with another. In order to identify the marginal effects of firm and forecast characteristics on forecast accuracy, Panel B of Table 4 reports the regression of the squared forecast error on the natural logarithm of market capitalisation, market-to-book, price-earnings and forecast earnings growth. Interestingly, all four variables independently contribute to the explanation of forecast accuracy, with the most influential, in terms of statistical significance, being the price-earnings ratio, followed by the level of the forecast itself. The most accurate forecasts are therefore low forecasts issued for large companies with low price-earnings ratios and high market-to-book ratios. The four variables together explain more than thirteen percent of the variation in forecast accuracy.

The variation of forecast accuracy with market capitalisation is not surprising. Information about future earnings prospects is likely to be more readily available, and of a higher quality, for larger firms. The variation of forecast accuracy with the forecast itself is consistent with the results on forecast efficiency. The inverse relationship between forecast accuracy and price-earnings ratio is harder to explain, but may be driven by the fact that very