1990

On analysts' earnings forecast for failing firms

Moses, O. Douglas

Journal of Business Finance & Accounting, Volume 17, Issue 1, Spring 1990
https://hdl.handle.net/10945/44173

Journal of Business Finance & Accounting, 17(1) Spring 1990, 0306 686X $2.50

ON ANALYSTS' EARNINGS FORECASTS FOR FAILING FIRMS

O. DOUGLAS MOSES*

Much research has been conducted on the properties of analysts' earnings forecasts (AEF) and their information content in the context of the securities market. Broad conclusions are that AEF reflect a wide range of information, are relatively accurate and are associated with market returns and risk. Little research has been conducted on how the properties of AEF differ between different classes of firms and on whether AEF are useful in predicting events outside of the securities market. The general issues of interest in the study are how well AEF reflect different conditions faced by firms and how well measures based on AEF perform as indicators of future events. These issues are addressed by focusing on a particular class of firms, those that are failing. The specific objective is to examine differences in AEF between failing and healthy firms, and investigate whether measures developed from AEF are useful indicators of impending bankruptcy.

PRIOR RESEARCH ON AEF

Considerable prior research has examined the properties of AEF, their accuracy, and their relationship to the securities market. (For reviews, see Givoly and Lakonishok, 1984; and Brown, et al., 1985). Research on the ability of analysts to predict future earnings for firms indicates that AEF are generally superior to time series models based on past reported earnings (Barefield and Comiskey, 1975; Brown and Rozeff, 1979; and Collins and Hopwood, 1980) and show that AEF reflect information not captured by historical earnings trends (Fried and Givoly, 1982). Analysts revise their forecasts in a timely manner and apparently are able to separate a permanent from a temporary component in reported earnings numbers (Critchfield, et al., 1978). Furthermore, the superiority of AEF over time series models is more pronounced in years where there is a turning point in the earnings trend (Barefield and Comiskey, 1975). These findings suggest that AEF are a comprehensive piece of information which capture information that is external to firms' accounting systems.

* The author is Associate Professor in the Department of Administrative Science, Naval Postgraduate School, Monterey. Data on earnings forecasts used in this study were taken from the Institutional Brokers Estimate System (IBES) published by Lynch, Jones, and Ryan, New York. Access to historic IBES data provided by Lynch, Jones, and Ryan is greatly appreciated. Support for this project was provided by the Naval Postgraduate School Foundation Research Program, which is funded by the Office of Naval Research and the Office of Naval Technology. (Paper received June 1987, revised October 1987).

Research on the relationship between AEF and the securities market has documented an association between AEF and revisions in AEF with stock prices and has provided evidence that favorable trading strategies based on AEF can be developed (Niederhoffer and Regan, 1972; Givoly and Lakonishok, 1979 and 1980; and Elton, et al., 1984). Studies suggest that AEF are a better surrogate for the market expectation of earnings than are naive predictions based on historical earnings (Malkiel, 1970; Malkiel and Cragg, 1970; and Fried and Givoly, 1982). In short, AEF are useful indicators of expected performance in the securities market.

Of particular interest in the current context is research on measures of risk derived from AEF. The error in earnings forecasts has been shown analytically to be an appropriate indicator of uncertainty (Cukierman and Givoly, 1982), while the dispersion of forecasts across analysts and the unpredictability of earnings has been shown empirically to be associated with traditional risk measures such as beta and the standard deviation of returns (Givoly and Lakonishok, 1983). The dispersion of AEF has also been shown to be superior to measures of beta, economy risk, information risk, and interest rate risk in explaining expected return (Malkiel, 1981). Consequently, dispersion and unpredictability in AEF may serve as useful indicators of risk.

In short, analysts' earnings forecasts are forward looking, reflective of a broad information set, and provided and revised in a timely manner. AEF can be expected to reflect macroeconomic events, industry expectations and firm-specific non-accounting information. AEF are associated with future returns and capture aspects of risk. Earnings is considered the single most important expectational data item by investors (Chang and Most, 1980) so there is considerable attention and importance attached to AEF. For these reasons, AEF may differ systematically across firms depending on the conditions faced by the firms and AEF may reflect information relevant to predicting future events (aside from their well-documented relevance in stock valuation). More specifically, AEF may reflect conditions that lead to failure and may be potentially useful in indicating future bankruptcy. Subsequent sections address three distinct but related issues:

(1) The nature of AEF for failing firms. Do forecasts appear to reflect conditions associated with failure?

(2) The quality of AEF for failing firms. How well do forecasts estimate actual earnings for failing firms?

(3) The information content of AEF. Can AEF measures be used to predict future failure?

SAMPLE AND NOTATION

Firms declaring bankruptcy from 1977 through 1985 were identified from the *F & S Index of Corporate Changes* and the *Wall Street Journal Index*. A test period of four years prior to bankruptcy was defined and AEF data were collected from the Institutional Brokers Estimate System (IBES) for sample firms during the test period. IBES contains summary statistics related to annual earnings per-share forecasts from multiple forecasters who report their predictions to the IBES service. Each month IBES provides information on the mean forecast, median forecast, high forecast, low forecast, standard deviation of forecasts, actual reported earnings in prior years, and a number of other forecast related data. IBES contained data in years prior to failure for 68 firms that declared bankruptcy during the test period.[1]

Using rankings provided in the annual *Wards Directory of Leading US Corporations*, each brankrupt firm was matched with a non-bankrupt firm from the same industry and of approximately the same size[2] resulting in a total sample of 136 firms.[3]

The notation used in the paper refers to fiscal years. Two time related items are important: the year in which bankruptcy is declared for a bankrupt firm and the month relative to fiscal year-end within any year. The notation used treats bankruptcy as time 'zero' and counts backward in time such that both years and months increase as the time before bankruptcy or year-end increases. Year zero is the year in which bankruptcy was declared for a failing firm (and the corresponding fiscal year for the corresponding healthy firm in a matched pair). Year one is the fiscal year immediately prior to the year in which bankruptcy was declared. Within any given fiscal year, month zero is the last month in the year (e.g. December for a firm with December 31 year-end). Month three is three months prior to year-end (e.g. September), and so on. AEF for four years prior to bankruptcy at three month intervals corresponding to the end of the quarters were examined.

MEASURES FROM ANALYSTS' FORECASTS

Four properties of AEF were investigated:

1. The average forecasted earnings per share provided by analysts (EPS).
2. The dispersion or disagreement in forecasts across multiple analyst forecasters (DISP).
3. The accuracy or error in forecasts when compared to actual reported earnings (ERROR).
4. The bias in forecasts — whether they under or over predict actual earnings (BIAS).

Measures[4] to reflect the four properties were calculated as follows:

1. $\mathrm{EPS}_{tm} = \hat{Y}_{tm}$
2. DISP_{tm} = Standard deviation of forecasts for year t at month m across multiple forecasters.
3. $\mathrm{ERROR}_{tm} = |\hat{Y}_{tm} - Y_t|$

4. $\text{BIAS}_{tm} = \hat{Y}_{tm} - Y_t$

where $\hat{Y}_{tm}$ = Mean Forecasted earnings per share for year t provided at month m,

Y_t = Actual reported earnings per share for year t,

t = 1, 2, 3 or 4 (years prior to bankruptcy),

m = 0, 3, 6 or 9 (months prior to year end).

These properties may change over time. To reflect how the properties change across years (year-to-year changes), the difference between measures taken at month 0 in successive years was determined.[5] For example, to reflect the year-to-year change in forecasted EPS:

$$\text{EPSCHANGE}_t = \text{EPS}_{t,0} - \text{EPS}_{t-1,0}$$

Analogous measures reflecting year-to-year changes in forecast error (ERROR-CHANGE), forecast dispersion (DISPCHANGE) and forecast bias (BIASCHANGE) were developed.

To reflect how the properties change within a given forecast year (within year trends), the difference between measures taken at mid-year (month 6) and year-end (month 0) was computed.[6] For example, to reflect the trend in EPS:

$$\text{EPSTREND}_t = \text{EPS}_{t,0} - \text{EPS}_{t,6}$$

An analogous measure reflecting the within year trend in forecast dispersion (DISPTREND) was developed.[7]

ON THE NATURE OF FORECASTS FOR FAILING FIRMS

Broadly speaking, future performance for firms can be described by two constructs: risk and expected return. As indicated above, AEF measures have been shown to be associated with both risk and return. If failing and healthy firms differ in their risk and return characteristics, one would expect systematic differences in their AEF properties. Two measures, EPS and DISP, reflect aspects of expected performance and risk, respectively.

EPS: Although low earnings does not imply bankruptcy and high earnings does not insure health, one would expect some relationship between the level of earnings and the probability of future failure. While reported earnings may contain information relevant to distinguishing between groups, forecasted earnings is future looking and consequently has the potential to reflect aspects of firm health that have not yet been reflected in reported earnings. If conditions that lead to failure are reflected in AEF one might expect failing firms to have (a) lower forecasted earnings, and (b) declining forecasted earnings as failure approaches.

Table 1 shows group means for the EPS variables and non-parametric Wilcoxon rank sum tests of significance for group differences (equivalent to

Table 1

Group Differences in Forecasted EPS Measures

			Group Means		Wilcoxon	
Variable	*Year*	*Month*	*Failing*	*Healthy*	*Z*	*α*
EPS	1	0	−0.86	1.57	−6.17	0.000
		3	−0.27	1.77	−6.15	0.000
		6	0.44	1.95	−4.91	0.000
		9	0.88	2.02	−4.23	0.000
	2	0	−0.81	1:69	−4.94	0.000
		3	0.07	1.87	−4.25	0.000
		6	0.58	2.10	−3.36	0.001
		9	1.24	2.14	−2.99	0.003
	3	0	0.22	1.91	−3.14	0.002
		3	0.95	1.97	−1.97	0.049
		6	1.24	2.07	−1.62	0.105
		9	1.78	2.20	−1.06	0.291
	4	0	1.11	1.96	−1.78	0.075
		3	1.59	1.97	−0.89	0.373
		6	2.09	1.93	−0.09	0.924
		9	2.33	1.82	0.21	0.835
EPSTREND	1		−1.34	−0.29	−3.75	0.000
	2		−1.51	−0.27	−3.66	0.000
	3		−1.05	−0.08	−2.26	0.024
	4		−0.93	0.09	−1.78	0.076
EPSCHANGE	1		−0.08	−0.03	−2.54	0.011
	2		−1.46	−0.09	−3.07	0.002
	3		−1.01	0.09	−1.96	0.049

Mann-Whitney *U* Tests). Both expectations appear to hold. Failing firms have lower forecasted EPS up to about $3\frac{1}{2}$ years prior to failure and significantly lower EPS ($\alpha \leq 0.05$) for about $2\frac{1}{2}$ years. Group differences in how EPS changes over time are also apparent. There are consistent negative value for EPSTREND and EPSCHANGE for failing firms, indicating declining forecasts both within individual years and from year to year. Although values for EPSTREND and EPSCHANGE also tend to be negative for the healthy firms, the Wilcoxon tests indicate that the declines are significantly greater for the failing group.

DISP: Dispersion or disagreement across multiple forecasters has been shown to reflect uncertainty or risk. Givoly and Lakonishok (1984) see AEF dispersion measures as 'unique' because unlike most traditional measures of risk, they are 'ex ante' measures. Two aspects of risk or uncertainty may be relevant for failing firms. One, financial risk or uncertainty, refers to the inability of a firm to pay its debts as they become due (see for example, Block and Hirt, 1987). The second, which might be termed information risk or uncertainty, refers to the tendency for misleading or confusing information to appear concerning firms in distress. If failing firms become financially more risky as failure approaches and/or there is increased uncertainty concerning the quality of information for firms in distress, and this uncertainty is reflected in AEF, one would expect failing firms to have (a) greater dispersion in forecasts and (b) increasing dispersion as failure approaches.

Table 2 shows group means for dispersion measures. Except for month 9 of year 3, forecast dispersion is consistently greater for the failing group. These group differences are most pronounced at the end of each forecast year and

Table 2

Group Differences in Forecast Dispersion Measures

			Group Means		*Wilcoxon*	
Variable	*Year*	*Month*	*Failing*	*Healthy*	*Z*	α
DISP	1	0	0.66	0.22	3.10	0.002
		3	0.49	0.23	2.94	0.003
		6	0.44	0.25	3.38	0.001
		9	0.44	0.24	2.29	0.022
	2	0	0.66	0.19	2.01	0.044
		3	0.43	0.25	2.59	0.013
		6	0.29	0.25	1.69	0.092
		9	0.31	0.29	1.18	0.238
	3	0	0.27	0.18	2.47	0.013
		3	0.41	0.21	1.73	0.083
		6	0.47	0.29	1.13	0.257
		9	0.20	0.24	−0.02	0.981
	4	0	0.29	0.13	1.59	0.112
		3	0.32	0.14	1.28	0.200
		6	0.30	0.22	0.61	0.540
		9	0.25	0.19	1.14	0.251
DIPSTREND	1		0.22	−0.03	0.31	0.757
	2		0.42	−0.04	1.78	0.074
	3		0.05	−0.08	1.16	0.244
	4		−0.03	−0.08	0.23	0.815
DISPCHANGE	1		0.29	0.05	1.92	0.054
	2		0.50	0.05	0.32	0.752
	3		0.01	0.06	1.10	0.269

become significant as early as three years prior to failure. Thus forecast dispersion may capture uncertainty associated with impending failure.

Findings for changes in dispersion over time are mixed. Except for year 4, DISPTREND and DISPCHANGE are positive for the failing firms, indicating consistently increasing dispersion, both within and across years, in the three years prior to failure. This finding would be expected if uncertainty increases as failure approaches. However, signs for DISPTREND for the healthy group are also positive and group differences for both DISPTREND and DISPCHANGE are not significant.

ON THE QUALITY OF FORECASTS FOR FAILING FIRMS

In a review of research on AEF, Givoly and Lakonishok (1984) discuss the rationality (Muth, 1961) of analysts forecasts and evaluate AEF in terms of their rationality. They state that if AEF are rational they should be 'unbiased' and 'most accurate'. Unbiased implies no systematic error; most accurate implies, among other things, superiority over time series forecast models using reported earnings. They conclude that, in general, evidence supports rationality for AEF; AEF tend to be more accurate than time series forecast models (and incorporate information on past reported earnings and past forecast errors), and are not significantly biased. The issue of interest here is whether forecasts for failing and healthy firms differ with respect to accuracy and bias.

ERROR. Two tests concerning the accuracy of analysts forecasts were conducted. The first addresses whether AEF, for failing firms in particular, are 'most accurate'; the second compares the accuracy of AEF for failing firms as compared to healthy firms.

First, to test if AEF are 'most accurate', forecast errors using analysts' forecasts were compared to forecast errors using a naive (no change) forecast. Recall that AEF error was previously measured as

$$\text{ERROR}_{tm} = |\hat{Y}_{tm} - Y_t|.$$

Similarly, errors using a naive model were constructed as

$$\text{Naive Error}_t = |Y_{t-1} - Y_t|.$$

A simple difference between the two types of error provides a measure[8] indicating which prediction source is superior to the other:

$$\text{Error Difference}_{tm} = |Y_{t-1} - Y_t| - |\hat{Y}_{tm} - Y_t|.$$

Positive (negative) values indicate analyst superiority (inferiority) to the naive forecast.

Group means and t tests of significant difference from zero for failing and healthy firms are shown in Table 3. Error differences for both groups are positive throughout the three years prior to failure, so on average AEF are superior

Table 3

Forecast Error Differences: Analysts' Forecast vs Naive Model

		Failing			Healthy		
Year	*Month*	*Mean*	*t*	*α*	*Mean*	*t*	*α*
1	P*	0.61	0.86	0.400	0.54	4.30	0.000
	0	0.35	0.58	0.565	0.51	3.96	0.000
	3	0.46	0.80	0.435	0.37	3.45	0.001
	6	1.27	1.53	0.145	0.22	1.97	0.054
2	P	1.14	2.98	0.006	0.34	4.09	0.000
	0	0.96	2.74	0.010	0.29	3.51	0.001
	3	0.44	2.11	0.043	0.15	1.62	0.111
	6	0.05	0.27	0.786	0.10	1.29	0.203
3	P	1.24	1.77	0.086	0.36	2.67	0.010
	0	1.30	1.75	0.090	0.36	2.57	0.013
	3	0.63	1.42	0.165	0.29	2.20	0.032
	6	0.33	0.73	0.472	0.14	1.22	0.228

*P = Month immediately prior to announcement of actual reported earnings.

to the naive forecast. But the degree of superiority differs between the two groups. In the latter months of each year, and after year-end at the month immediately prior to announcement of actual reported earnings (month 'P' in the table), AEF for the healthy group are significantly more accurate than naive forecasts.

Analyst superiority over naive forecasts is considerably less impressive for the failing firms. *T* values are lower for the failing group and generally insignificant except in the latter months of year 2. The contrast between the two groups is most pronounced in the year immediately prior to failure; analysts are unable to out-predict the naive model for failing firms, even in the month immediately before announcement of earnings, at any reasonable level of significance.

The second test asks whether there are systematic differences in the magnitude of forecast errors between failing and healthy firms. As indicated earlier forecast errors have been shown to reflect uncertainty and risk. If firms become more risky as failure approaches and this uncertainty is reflected in AEF, one would expect failing firms to have (a) larger forecast errors, and (b) increasing errors as failure approaches.

Table 4 shows group means for ERROR and ERRORCHANGE measures and Wilcoxon tests for significant differences between the groups. ERROR values are consistently larger for failing firms and significantly so as early as year 4. This is consistent with larger forecast errors reflecting the greater risk of the failing firms. ERRORCHANGE values indicate a particularly large

Table 4

Group Differences in Forecast Error Measures

			Group Means		*Wilcoxon*	
Variable	*Year*	*Month*	*Failing*	*Healthy*	*Z*	*α*
ERROR	1	0	4.17	0.40	5.97	0.000
		3	5.16	0.55	5.46	0.000
		6	6.63	0.72	5.95	0.000
		9	6.66	0.89	6.01	0.000
	2	0	1.40	0.43	3.27	0.001
		3	2.07	0.58	3.86	0.000
		6	2.10	0.63	3.51	0.001
		9	2.97	0.75	3.00	0.003
	3	0	0.86	0.34	3.76	0.000
		3	1.52	0.44	3.39	0.001
		6	1.89	0.64	2.54	0.011
		9	2.59	0.77	2.18	0.029
	4	0	0.62	0.26	2.59	0.010
		3	0.91	0.39	1.72	0.085
		6	1.70	0.56	2.42	0.016
		9	2.21	0.77	1.50	0.134
ERRORCHANGE	1		3.65	0.05	2.92	0.004
	2		0.07	0.14	1.23	0.218
	3		0.17	0.10	0.67	0.500

increase in forecast errors for the failing group from year 2 to year 1. This is consistent with increasing uncertainty as bankruptcy approaches being reflected in increasing forecast errors.

BIAS. Studies by Critchfield et al. (1978), Givoly (1985), and Malkiel and Cragg (1980) have failed to reject the hypothesis that AEF are unbiased. However there is reason to expect differences in bias between failing and healthy firms. There is some evidence that firms tend to withhold 'bad' news in hope or anticipation of improvement (Penman, 1980). Hence, the pattern of information released to analysts may differ for failing firms. If failing firms experience worse performance and news of that experience is withheld (until disclosed in the reported earnings number), over-optimistic forecasts should result. Consequently, failing firms should have (a) more positive values for BIAS. If the 'bad' news is more pronounced the closer to actual failure, failing firms could have (b) increasing bias from year-to-year.

Table 5 displays group means for BIAS and tests of significant difference from zero. While there is occasional evidence of a significant positive bias for healthy firms in the early months of some years, BIAS values are small and

Table 5

Significance of Forecast Bias, by Groups

		Failing Firms			*Healthy Firms*		
Year	*Month*	*Mean*	*t*	*α*	*Mean*	*t*	*α*
1	P*	3.06	2.78	0.009	−0.06	−0.54	0.594
	0	3.93	3.40	0.002	0.00	0.04	0.971
	3	5.09	4.11	0.000	0.18	1.59	0.118
	6	6.63	4.73	0.000	0.27	1.95	0.056
	9	6.66	4.99	0.000	0.36	2.21	0.031
2	P	0.85	1.65	0.108	0.15	1.23	0.225
	0	1.03	2.12	0.042	0.17	1.34	0.185
	3	1.86	3.48	0.001	0.33	2.34	0.023
	6	2.05	5.02	0.000	0.43	3.15	0.003
	9	2.87	3.62	0.001	0.50	3.38	0.001
3	P	0.50	2.71	0.010	0.05	0.77	0.445
	0	0.68	3.51	0.001	0.12	1.39	0.171
	3	1.36	2.62	0.013	0.16	1.45	0.152
	6	1.70	2.61	0.015	0.22	1.37	0.177
	9	2.35	2.37	0.025	0.35	1.83	0.074
4	P	−0.08	−0.41	0.682	0.02	0.31	0.761
	0	−0.14	−0.63	0.536	0.02	0.21	0.834
	3	0.31	1.08	0.292	0.00	0.02	0.986
	6	1.07	1.81	0.083	−0.07	−0.51	0.616
	9	1.32	1.63	0.118	−0.18	−1.00	0.325

*P = Month immediately prior to announcement of actual reported earnings number.

insignificantly different from zero in the latter months and in the month just prior to announcement in all years. Analysts have available sufficient information on healthy firms to produce unbiased forecasts by year-end.

BIAS values for the failing group are consistently larger for three years prior to failure and, except for month P in year 2, are significantly positive throughout that three year period. Thus forecasts for failing firms are significantly optimistic. Even by year-end, analysts do not have available sufficient information to produce unbiased forecasts.

While BIAS values for the failing group are larger than for the healthy group, both are positive. Are BIAS values significantly greater for failing firms? Table 6 provides Wilcoxon tests for group differences. Results indicate significantly greater bias up through three years prior to failure. While not statistically different from the healthy group, the failing group also has a large BIASCHANGE measure in year 1, suggestive of an increase in bias from year 2 to year 1. In short, results show significantly over-optimistic forecasts for failing firms

Table 6

Group Differences in Forecast Bias Measures

			Group Means		Wilcoxon	
Variable	*Year*	*Month*	*Failing*	*Healthy*	*Z*	α
BIAS	1	0	3.93	0.00	4.69	0.000
		3	5.09	0.18	5.53	0.000
		6	6.63	0.27	6.22	0.000
		9	6.66	0.36	6.29	0.000
	2	0	1.03	0.17	2.97	0.003
		3	1.86	0.33	4.06	0.000
		6	2.05	0.43	3.92	0.000
		9	2.87	0.50	3.18	0.002
	3	0	0.68	0.12	3.21	0.001
		3	1.36	0.16	2.84	0.005
		6	1.70	0.22	2.47	0.016
		9	2.35	0.35	2.11	0.035
	4	0	−0.14	0.02	−0.34	0.734
		3	0.31	−0.00	0.56	0.579
		6	1.07	−0.07	0.95	0.342
		9	1.32	−0.18	1.22	0.224
BIASCHANGE	1		3.99	−0.07	1.89	0.058
	2		−0.17	0.07	−0.44	0.661
	3		0.83	0.17	1.83	0.067

for three years and suggest some increase in over-estimation in the year just prior to failure.

A comment on the implications of this apparent bias is perhaps necessary. Does the presence of a bias imply irrational forecasts? Both Critchfield et al. (1978) and Givoly and Lakonishok (1984) indicate that rational forecasts should be unbiased. Yet there are two possible explanations for the observed bias for the failing group. First, forecasters could have failed to properly incorporate information available to them at the time of the forecast. Second, analysts could have properly incorporated available information but information indicating that forecasts were optimistic was not available at the time of the forecast (i.e. 'bad' news was withheld).

To investigate the first possibility, two tests, modeled after those conducted by Givoly (1985), were conducted for the years prior to failure. Partial correlations between Y_t and Y_{t-1} (given EPS_t) were computed. This is a test of whether past earnings contain information related to future earnings that is not incorporated into forecasts. The partial correlations were generally insignificant. This finding is consistent with analyst use of the information contained in historical earnings. Next, tests of serial correlation between forecast errors were conducted. Correlations were insignificant. This finding is consistent with analyst incorporation of the information contained in past forecast errors. In short there was no evidence of failure to use information available in historical earnings and past forecast errors.

To investigate the second possibility, correlations between the change in reported earnings from year to year ($Y_t - Y_{t-1}$) and $BIAS_t$ were computed. Correlations were consistently high, significant and negative (ranging from -0.93 to -0.61 over years 1–3). This indicates that as the decline in earnings gets larger, forecasts become more over-optimistic. This finding is consistent with firms withholding bad news. It is inconsistent with arguments offered by some (e.g. Ajinkya and Gift, 1984) that firms have incentives to disclose information, both good and bad, to 'correct' erroneous analyst forecasts. In short, the additional tests are more supportive of the view that the observed bias was due to lack of information, not failure to use available information.

ON THE PREDICTIVE CONTENT OF AEF MEASURES

Collectively the findings indicate that measures of the four forecast properties investigated differ systematically between healthy and failing firms in years prior to failure.

Can these systematic differences be used to predict failure? The most common source of information for assessing financial health and predicting failure is financial ratios taken from accounting reports (see Zavgren, 1983, for a review). There are, however, several weaknesses in using accounting data. Accounting data are produced only periodically, are historical rather than prospective, and reflect events that are primarily endogenous to the firm. Accounting measures are sensitive to the choice of accounting procedures, subject to 'window dressing', and inevitably vary in magnitude across firms and industries as a function of the nature of operations and technology. Perhaps alternative failure indicators, to supplement the use of accounting ratios, can be developed from AEF measures.

There were ten different kinds of measures (reflecting four properties of AEF and how those properties change over time) that were previously calculated. To investigate predictive ability, one measure of each kind was selected. The above tests indicate that the differences between failing and healthy firms become more pronounced as failure approaches, so the measures were selected to emphasize the period shortly before bankruptcy. $EPS_{1,0}$; $DISP_{1,0}$; $ERROR_{1,0}$; and $BIAS_{1,0}$ are measures of the four primary properties at year-end in year 1. $ERRORCHANGE_1$ and $BIASCHANGE_1$ capture the relatively large increases in forecast error and bias that occurred for failing firms from year 2 to year 1. $EPSCHANGE_1$ and $EPSTREND_2$ together capture the change in EPS over the $1\frac{1}{2}$ years prior to the bankruptcy year.

$DISPCHANGE_1$ and $DISPTREND_2$ together capture the change in DISP over the same $1\frac{1}{2}$ year period. In short, these ten measures, reflect the four AEF properties and their changes over time shortly before bankruptcy.

To test predictive ability, the ten measures were combined in a 'failure index'. By far the most popular approach for combining variables into a bankruptcy classiciation or prediction model has been multivariate discriminant analysis. (See Zavgren, 1983, for a review). However, the use of discriminant analysis has been criticized (Moyer, 1977; and Eisenbeis, 1977). Moses and Liao (1986 and 1987) explain a procedure for combining multiple variables into a failure index that in their study out-performed discriminant models in predicting failure. A procedure analogous to Moses and Liao was used to create the index reported here.[9]

The procedure for creating the index included two basic steps: First, values for the ten individual variables were separately analyzed to provide independent univariate classifications of the sample firms into healthy or failing categories (this step is analogous to Beaver, 1966); second, the ten independent classifications were aggregated into an index and a final classification was based on the index. In more detail:

1. Firms were rank ordered independently on each of the ten individual variables. The rank ordered values for a given variable were then visually observed and a threshold value for each variable was selected to divide sample observations into failing and healthy firms. Threshold values were selected that minimized the percentage of firms misclassified. For example, EPS values for the sample firms ranged from −9.50 to 6.46, with failing firms clustered toward the lower values. Selecting a threshold of 0.11 and classifying firms below (above) the threshold as failing (healthy) minimized misclassifications (and resulted in a classification error rate of 22 per cent for the sample.)[10]

2. Next, for each of the ten variables, a firm was assigned a score of 1 if it fell on the 'bankruptcy' side of the threshold for the particular variable, and 0 otherwise. Then the ten scores were added for each firm into a total score (the index). This approach rests on the simple idea that a consensus prediction from multiple sources (i.e. the univariate signals) is typically more accurate than the individual sources (Beaver, 1981). If more of the variable values for a given firm fell on the bankruptcy side of the thresholds, a higher total index score resulted for the firm; index scores from zero to ten were possible. If the index is a useful classification tool, failing (healthy) firms should cluster toward higher (lower) index scores. Lastly, firms were rank ordered on their index scores and a threshold value for the index that minimized errors in classification was determined by viewing the ranking of index scores. (This process is analogous to that performed on the values for individual variables in step 1 above.) This index threshold provided the dividing line for classifying firms as failing or healthy.[11]

The overall classification error rate using this index approach was 4 per cent. Classification results, however, typically overstate the value of any approach

Table 7

Comparison of Failure Prediction Models

Study	Prediction Error Rates					
	Classification Tests			Validation Tests		
	*Type 1**	*Type 2***	*Overall*	*Type 1**	*Type 2***	*Overall*
AEF Index	8%	3%	4%	8%	3%	4%
Beaver (1966)	22%	5%	10%	—	—	13%
Altman (1968)	6%	3%	5%	4%	21%	16%
Deakin (1972)	3%	3%	3%	—	—	22%
Diamond (1976)	—	—	—	3%	10%	9%
Wilcox (1971)	—	—	—	—	—	6%
Blum (1974)	—	—	7%	4%	7%	5%
Altman et al. (1977)	7%	10%	9%	4%	10%	7%
Ohlson (1980)	12%	17%	15%	—	—	—
Zavgren (1982)	11%	24%	18%	—	—	—

* Type 1 error is misclassifying a failing firm as healthy.
** Type 2 error is misclassifying a healthy firm as failing.

in discriminating between two groups since the classification procedure (index) is applied to the same sample on which it is developed. Validation is required. Ideally, validity should be assessed on a sample unrelated to that used to develop the classification rule, a hold out sample. Operationally this was achieved by randomly dividing the sample into two subsamples, developing an index independently from each subsample, and using the index from each subsample to classify the firms in the other subsample. Classification errors in each of the two subsamples were than averaged to get error rates for the full sample.

There was no decline in predictive ability[12] from the validation procedure; overall error rate[13] remained at 4 per cent. One can compare this with various models using traditional accounting ratios as predictors that have appeared in the published literature. Zavgren (1983) reviewed nine published models and provided details, when available, on classification and validated error rates in the year immediately prior to failure. A comparative summary is provided in Table 7. The AEF failure index appears competitive with these models; in fact, its overall error rate of 4 per cent on the validation test is less than for any of the other models reported.[14]

CONCLUDING REMARKS

Collectively the findings indicate three things.

(1) Analysts' forecasts apparently do reflect conditions that are associated

with failure. Indicators of predicted performance (EPS) are lower and indicators of risk (DISP) are higher for failing firms, and both indicators change in the expected manner as failure approaches. These findings are not surprising but do confirm, for a particular class of firms, the general conclusion from prior research that analysts' forecasts are a useful, comprehensive data item updated over time to reflect changing conditions.

(2) Analysts' forecasts are of poorer quality for firms approaching failure. Forecast errors were larger and increased for failing firms as bankruptcy approached; forecasts were over-optimistic and bias increased for failing firms as bankruptcy approached. The larger forecast errors are not surprising since forecast errors have been shown to be related to uncertainty. The uncertainty is apparently great enough that forecasts for failing firms are not consistently significantly better than a naive (no change) forecast. The poor accuracy is due to significant over-estimation. This bias is probably caused not by failure of analysts to properly incorporate available information but rather by inability of analysts to obtain information that fully reflects the condition of firms approaching failure. Failing firms may withhold bad news.

(3) Measures developed from analysts' forecasts do have information content for predicting future states of firms, specifically bankruptcy. While most past research has, not unreasonably, explored the usefulness of analysts' forecasts in the context of the securities market, the findings here suggest their potential value in other areas of prediction.

There are several directions for future research. Those interested in the properties of forecasts may wish to further explore the issue of bias. Both Givoly (1985) and Critchfield et al. (1978) detected no substantial forecast bias in their studies. Although their samples were more representative of the population of all firms, they were not fully representative in that firms with poor (i.e. negative) earnings were deleted. The findings here indicate that the properties of forecasts may differ for such groups and may be a function of information disclosure practices of firms. Those interested in the process by which information is released by firms and the ability of analysts to obtain information may find firms in poor health an informative sample to investigate.

Those interested in bankruptcy prediction may wish to further investigate the use of AEF measures. While additional kinds of measures and models involving AEF could be explored, the most interesting direction may be to address the relative or incremental predictive ability of AEF measures when compared to traditional accounting ratios. The fact that analysts' earnings forecasts do reflect failure relevant information and, being forward looking, have the potential to reflect evolving events prior to the publication of financial statements, indicates that signals provided by analysts' earnings forecasts might be used as an early warning of failure in conjunction with traditional reliance on financial accounting ratios.

More generally, those interested in prediction of various future events may find analysts' forecasts a potential source of predictive indicators. The findings of this study indicate systematic differences in AEF properties consistent with firm differences in expected performance, risk and information disclosure. The fact that a model using AEF measures to predict failure was competitive with models using accounting ratios suggests that AEF measures have useful information content in areas outside of their traditional role in stock valuation.

NOTES

1 The distribution of the 68 bankrupt firms across calender years was as follows: 1985 (14), 1984 (19), 1983 (9), 1982 (13), 1981 (7), 1980 (3), 1979 (2), 1977 (1).

2 Matching on industry is desirable to control for industry characteristics and conditions. Forecast uncertainty may be related to industry. Furthermore, information events may have industry-wide implications leading to industry-wide revisions in earnings forecasts.

Matching on size is desirable because size is associated with risk, probability of bankruptcy, analyst attention, and most likely, the number of sources from which consensus forecasts and summary statistics on the IBES tape are developed. Using total assets (sales) as a measure of size, 58% (50%) of bankrupt firms were larger than their non-bankrupt matched firm. Tests revealed no significant difference in mean size between bankrupt and non-bankrupt groups.

Matching on fiscal year-end would perhaps be desirable but was not possible without a great reduction in sample size. Data for each firm in a given matched pair were however taken from the same fiscal year. Within a given year there is substantial evidence that the properties of analysts' forecasts change as the year-end approaches. For example, forecasts tend to become more accurate as the end of a reporting year approaches. However, data in the study was analyzed in terms of fiscal years rather than calender years, which minimizes any problems associated with firms having different fiscal year-ends.

3 The 68 pairs, 136 firms, represent the maximum sample available for the analysis conducted. However, data for each firm was not available on IBES for each month and year of the test period, so some tests were conducted on sample sizes less than 136.

4 Each of these measures uses the mean forecasted EPS as the average forecast across forecasters. Tests using the median were also conducted.

Each of these measures also uses undeflated EPS values. It may be argued that adjustment for magnitude differences in EPS may be desirable. Tests deflating by stock price and by prior years reported earnings were conducted.

In addition to the standard deviation, alternative measures of the dispersion of forecasts, such as the variance and range as well as versions of these measures deflated by price and EPS, were also investigated. Tests using all of the above alternatives provided findings similar to those reported here for the simpler undeflated measures.

5 Year-to-year changes can be calculated using forecasts from any month within a given year. Because forecasts are not available for some firms in the early part of a given year, year end forecasts were used to maximize sample size.

6 A six month period was in general adequate to capture the within year trends. The six months at the end of a forecast year was used to allow sufficient time for release of the previous year's reported earnings.

7 Analogous within year trend measures for BIAS and ERROR can be calculated but they are a function of EPSTREND and thus are redundant.

8 This is simply the undeflated difference in forecast error. Other error difference measures were computed by deflating by (a) reported earnings, (b) forecast error from the naive model, (c) stock price, and by computing (d) a log relative measure (ln (analyst forecast error/naive forecast error)). Each alternative provided the same findings. Additional tests were also conducted using a random walk with a drift as a naive model. Findings did not change.

9 Discriminant models were constructed but were inferior to the index approach.

10 Univariate classification error rates ranged from 13 per cent to 29 per cent across the 10 variables. One can test for statistical significance by comparing the error rates from this univariate threshold approach with error rates resulting from a random assignment of firms to categories. (See t-test described by Altman, 1983, p. 113). Classification results for all 10 variables were statistically superior to random assignment at $p < 0.10$.

11 Index scores ranged from 0 to 8. All firms with index scores of 0 or 1 were healthy; all with index scores of 4 or more ultimately failed. Firms with index scores of 2 or 3 were a mixture of failing and healthy, a gray area. The optimal threshold was between 2 and 3.

12 Most bankruptcy researchers assess the predictive ability of their models relative to results achieved by random assignment of firms to categories. A t test, analogous to that referred to in footnote 10, found the index significantly superior to random assignment at $p < 0.001$.

13 There are limitations to evaluating a predictive model in terms of overall classification error rate. Such an approach ignores the relative costs of type 1 and type 2 errors. Furthermore, classification error rates in bankruptcy studies, even when validated on a holdout sample, typically understate the rates that would occur if the model were applied to a true population because the proportion of failing firms in the sample used to evaluate the model is greater than the proportion found in a true population (Wood and Piesse, 1987). The objective here is not to develop an optimal model or advance the state of the art in failure prediction models. The index created here is just a medium for testing the potential predictive content of AEF based measures.

14 While the AEF index is quite successful in predicting failure in the year prior to bankruptcy, it is less successful in earlier years. This is not surprising. The index includes several variables measuring within year trends and year-to-year changes in AEF measures. Group differences for these changes were less pronounced in earlier years. For the studies reviewed by Zavgren overall validated error rates in year 2 (year 3) ranged from 6%–21% (12%–30%). Indexes using AEF measures achieved overall validated error rates in year 2 (year 3) of 23% (25%).

REFERENCES

Abdel-Khalik, A. and B. Ajinkya (1982), 'Returns to Informational Advantages: The Case of Analysts' Forecast Revisions', *Accounting Review* (October 1982), pp. 661–80.

Ajinkya, B. and M. Gift (1984), 'Corporate Managers' Earnings Forecasts and Symmetrical Adjustments of Market Expectations', *Journal of Accounting Research* (Autumn 1984), pp. 425–444.

Altman, E. (1983), *Corporate Financial Distress* (John Wiley and Sons, New York, 1983).

______ (1968), 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy', *The Journal of Finance* (September 1968), pp. 589–609.

______, R. Haldeman and P.Narayanan (1977), 'Zeta Analysis', *Journal of Banking and Finance* (June 1977), pp. 29–54.

Barefield, R. and E. Comiskey (1975), 'The Accuracy of Analysts' Forecasts of Earnings Per Share', *Journal of Business Research* (July 1975), pp. 241–52.

Beaver, W. (1981), *Financial Reporting: An Accounting Revolution*, (Prentice-Hall, Englewood Cliffs, New Jersey, 1981).

______ (1966), 'Financial Ratios as Predictors of Failures', in *Empirical Research in Accounting*, selected studies, 1966, Supplement to *Journal of Accounting Research*.

Block, S. and G. Hirt (1987), *Foundations of Financial Management* (Irwin, Homewood, Illinois, 1987).

Blum, M. (1974), 'Failing Company Discriminant Analysis', *Journal of Accounting Research* (Spring 1974), pp. 1–25.

Brown, L. and M. Rozeff (1979), 'Adaptive Expectations, Time-Series Models and Analyst Forecast Revisions', *Journal of Accounting Research* (Autumn 1979), pp. 341–51.

Brown, P., G. Foster and E. Noreen (1985), *Security Analyst Multi-year Earnings Forecasts and the Capital Market* (Sarasota, Florida: American Accounting Association, 1985).

Chang, L. and K. Most (1980), 'Financial Statements and Investment Decisions', (manuscript, Florida International University, Miami, 1980).

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* (Autumn 1980), pp. 340–406.

Crichfield, T., T. Dyckman and J. Lakonishok (1978), 'An Evaluation of Security Analysts' Forecasts', *Accounting Review* (July 1978), pp. 651–68.

Cukierman, A. and D. Givoly (1982), 'Heterogeneous Earnings Expectations and Earnings Uncertainty – Theory and Evidence', working paper, Tel Aviv University (1982).

Deakin, E. (1972), 'A Discriminant Analysis of Predictors of Business Failure', *Journal of Accounting Research* (Spring 1972), pp. 167–79.

Diamond, H., Jr. (1976), 'Pattern Recognition and the Detection of Corporate Failure' (Ph.D. dissertation, New York University, 1976).

Eisenbeis, R. (1987), 'Pitfalls in the Applications of Discriminant Analysis in Business Finance and Economics', *Journal of Finance*, Vol. 32 (1987), pp. 875–900.

Elton, E., M. Gruber and M. Gultekin (1984), 'Professional Expectations: Accuracy and Diagnosis of Errors', *Journal of Financial and Quantitative Analysis* (December 1984), pp. 351–363.

Fried, D. and D. Givoly (1982), 'Financial Analysts' Forecasts of Earnings: A Better Surrogate for Earnings Expectations', *Journal of Accounting and Economics* (October 1982), pp. 85–107.

Givoly, D. (1985), 'The Formation of Earnings Expectations', *The Accounting Review* (July 1985), pp. 372–386.

______ and J. Lakonishok (1979), 'The Information Content of Financial Analysts' Forecasts of Earnings', *Journal of Accounting and Economics* (Winter 1979), pp. 165–85.

______ ______ (1980), 'Financial Analysts' Forecasts of Earning Their Value to Investors', *Journal of Banking and Finance* (September 1980), pp. 221–33.

______ ______ (1983), 'Divergence of Earnings Expectations: The Effect on Market Response to Earnings Signals', working paper 768/83, Faculty of Management, Tel Aviv University (February 1983).

______ ______ (1984), 'Properties of Analysts Forecasts of Earnings: A Review and Analysis of the Research', *Journal of Accounting Literature* (Spring 1984), pp. 117–152.

Gonedes, N. (1974), 'Capital Market Equilibrium and Annual Accounting Numbers: Empirical Evidence', *Journal of Accounting Research* (Spring 1974), pp. 26–62.

Malkiel, B. (1970), 'The Valuation of Public Utility Equities', *The Bell Journal of Economics and Management* (Spring 1970), pp. 143–60.

______ (1981), 'Risk and Return: A New Look', working paper, Lynch Jones, and Ryan, New York (April 1981).

______ and J. Cragg (1970), 'Expectations and the Structure of Share Prices', *American Economic Review* (1970), pp. 601–17.

______ ______ (1980), 'Expectations and the Valuation of Shares', working paper 471 (April 1980), National Bureau of Economic Research.

Moses, D. and S. Liao (1986), 'Predicting Bankruptcy of Private Firms: A Simplified Approach', *Proceedings*, Decision Sciences Institute 1986 Annual Meeting, pp. 212–214.

______ ______ (1987), 'On Developing Models for Failure Prediction', *Journal of Commercial Bank Lending* (April 1987), pp. 27–38.

Moyer, R. (1977), 'Forecasting Financial Failure: A Re-examination', *Financial Management* (Spring 1977), pp. 11–17.

Muth, J. (1961), 'Rational Expectations and Theory of Price Movement', *Econometrica* (July 1961), pp. 315–35.

Neiderhoffer, V. and P. Regan (1972), 'Earnings Changes, Analysts Forecasts and Stock Prices' *Financial Analysts Journal* (May–June 1972), pp. 65–71.

Ohlson, J. (1980), 'Financial Ratios and the Probabilistic Prediction of Bankruptcy', *Journal of Accounting Research* (Spring 1980), pp. 109–31.

Penman, S. (1980), 'An Empirical Investigation of Voluntary Disclosure of Corporate Earnings Forecasts', *Journal of Accounting Research* (Spring 1980), pp. 132–160.

Wilcox, J. (1971), 'A Simple Theory of Financial Ratios as Predictors of Failure', *Journal of Accounting Research* (Autumn 1971), pp. 389–95.

Wood, D. and J. Piesse (1987), 'The Information Value of MDA Based Financial Indicators', *Journal of Business Finance & Accounting* (Spring 1987), pp. 27–38.

Zavgren, C. (1982), 'An Analysis of the Relationship between Failure Likelihood and Certain Financial Variables for American Industrial Firms', working paper, Krannert Graduate School of Management, Purdue University (1982).

______ (1983), 'The Prediction of Corporate Failure: The State of the Art', *Journal of Accounting Literature* (Spring 1983), pp. 1–38.