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The Net Impact of Corporate Seasonality on the Accuracy of Earnings Forecasts Published by Financial Analysts

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THE NET IMPACT OF CORPORATE SEASONALITY ON THE ACCURACY OF EARNINGS FORECASTS PUBLISHED BY FINANCIAL ANALYSTS

Abstract

This study investigates the net impact of corporate seasonality (CS) on the accuracy of forecasts of quarterly earnings per share (EPS) published by financial analysts. Using a multivariate model to control for other factors, the results generally do not indicate an association between the degree of CS and EPS forecast accuracy.

The Net Impact of Corporate Seasonality on the Accuracy of Earnings Forecasts Published by Financial Analysts

1. Introduction

The potential impact of corporate seasonality (CS) on the reliability and usefulness of interim financial reports has been a source of concern.[1] Maingot (1983, p. 139), for example, warns that "seasonal fluctuations can cause amounts for one period to be misleading unless care is taken to explain seasonal effects." Corporations also have expressed concern over the "distortion caused by seasonal factors" (Leftwich, Watts and Zimmerman, 1981, p. 55). Given these concerns, APB Opinion No. 28 (AICPA, 1973) and SEC Accounting Series Release No. 177 (SEC, 1975) encourage highly seasonal companies to disclose the effects of seasonality on their accounting results. To accomplish this, various approaches, including seasonal adjustment, have been discussed as a means of providing such information (Frank, 1969; Foster, 1977, p. 2; FASB, 1978, par. 315). To date, however, such voluntary disclosures are rare and seasonal adjustment has not been adopted at the corporate level.[2]

The purpose of this study is to provide evidence on the potential need for measuring and disclosing the effects of seasonality on quarterly accounting results at the corporate level. Unlike the U.S. government, which seasonally adjusts much of its published time-series data (e.g., gross national product, corporate earnings, housing starts, consumer prices, and unemployment rate), corporations have not supplemented their quarterly disclosures with seasonally-adjusted data. Since an important objective of interim reporting is to provide information for predicting corporate earnings (FASB, 1978), this study investigates the net impact of CS on the accuracy of forecasts of quarterly earnings per share (EPS) published by financial analysts. CS effects are measured here in terms of EPS forecast errors and CS is defined as the degree (in percentage terms) of variability in quarterly accounting outputs which is attributable to the seasonal component in those time series.

Prior research has shown that (1) quarterly earnings typically have both a seasonal component and an adjacent component (e.g., Watts, 1975; Foster, 1977, Griffin, 1977; Brown and Rozeff, 1979; Bathke and Lorek, 1984), (2) investors take CS into account when using quarterly data to predict quarterly earnings (e.g., Foster, 1977; Bathke and Lorek, 1984), (3) EPS forecast accuracy varies by quarter (e.g., Collins, Hopwood and McKeown, 1984), and (4) investors react to unexpected quarterly earnings (e.g., Foster, 1977; Bathke and Lorek, 1984; Mendenhall and Nichols, 1988). However, no previous study has assessed the net impact of CS on financial analyst forecast (FAF) accuracy. The current study helps fill this void.[3] It is based on the premise that the degree of seasonality (a characteristic of time series data) might favorably or unfavorably affect FAF performance (an outcome based in part on such data). The net impact of CS on FAF performance is an empirical issue because it cannot be determined a priori. This aspect of the study is discussed in the next section.

2. Motivation

The seasonal component of an economic times series represents "the intrayear pattern of variation which is repeated constantly or in an evolving fashion from year to year" (Shiskin, Young and Musgrave, 1967, p. 1). Although seasonality represents pattern, which tends to improve forecast accuracy, "some believe that for a seasonal business, the variations in quarterly revenue and the difficulty in relating cost to revenue for parts of a year seriously impair the usefulness of any measure of interim period income from operations" (FASB, 1978, par. 311).

In this study, usefulness is assessed in terms of EPS forecast accuracy. Shillinglaw (1961, p. 223) cautioned that seasonality "may affect interim statements in such a way as to reduce their usefulness in income forecasting, and it is to these influences that we must devote our attention." To test this assertion, it is hypothesized that if CS affects EPS forecast accuracy it could do so in two directions, resulting in either lower (Alternative 1) or higher (Alternative 2) forecast errors across firms. In addition, it might have no real or observed effect on forecast errors across firms (Alternative 3).

Under Alternative 1, CS could <u>reduce</u> forecast errors if the CS component were predicted with a high degree of accuracy. Under this alternative, forecasters would be expected to adjust fully for CS effects on accounting results and to exploit this information to improve EPS forecasts. In seasonal firms, the CS component would be expected to lead to lower forecast errors, since the seasonal component represents pattern.

Under Alternative 2, CS could increase forecast errors if the CS component were predicted with a low degree of accuracy. Under this alternative, forecasters would find it difficult to identify and interpret the CS component. In seasonal firms, the CS component would lead to higher forecast errors, since it would contain estimation error.

Under Alternative 3, CS could have no effect on forecast errors across firms if both of the above effects existed and cancelled each other out among the firms sampled or CS errors were offset by other errors. This alternative is the null hypothesis.

Alternative 2 and Alternative 3 are plausible because the process of predicting corporate earnings remains subjective and accounting practices vary considerably across firms. The ability of individuals to adjust for CS is at issue because (1) predictions of a stochastic time-series, such as corporate earnings, involve judgment and (2) research has shown that individuals have difficulty estimating stochastic processes (Eggleton, 1976, 1982; Doktor and Chandler, 1988). This aspect of FAF performance is borne out by several recent studies which indicate that (1) FAFs are not necessarily unbiased (e.g., Ricks and Hughes, 1985; Biddle and Ricks, 1988; Lys and Sivaramakrishnan, 1988; Mendenhall and Nichols, 1988; O'Brien, 1988) and (2) FAFs do not completely dominate time-series models in terms of providing information used by investors (e.g., O'Brien, 1988). Together, these studies imply that a positive association between CS and FAF errors (Alternative 2) cannot be ruled out a priori because systematic forecast errors have been shown to exist in other contexts.

Alternative 2 also cannot be ruled out because the Financial Accounting Standards Board (FASB) has noted that the "ability of users of interim reports to ascertain turning points, or change in trend, is obscured if an enterprise is subject to significant seasonal influence" (FASB, 1978, par. 314). This statement implies that CS could be a problem in certain years when conditions are changing and extrapolation errors are more prevalent. It also implies that forecasters sometimes may have difficulty estimating the trend component of a seasonal time series. This would result in higher forecast errors for seasonal companies.

In effect, the current study serves to provide evidence that was called for by Foster (1977), who examined six extrapolative models to determine their relative predictive ability in terms of (1) predicting step-ahead quarterly sales, expenses, and earnings, and (2) estimating market associations with each forecast model. He found that seasonal time-series models were more closely associated with aggregate market reactions than nonseasonal time-series models and concluded that "the capital market appears to be adjusting for seasonality by employing a forecast model that incorporates seasonal patterns in quarterly earnings" (Foster, 1977, p. 18). He noted, however, that additional research would be required to examine further the various claims made by some individuals that seasonal earnings could be "misleading" and "confusing" to investors (Foster, 1977, p. 16). The current study is designed to serve this purpose by investigating the net impact of CS on EPS forecast errors.

3. Research Design

The current study uses two measures of seasonality: the degree of seasonality in sales (DSS) and the degree of seasonality in earnings (DSE).

Each measure represents the percentage of quarter-to-quarter variation explained by the seasonal component of each time series. The Census X-11 Model, which is discussed in Section 3.3.2, was used to generate these measures.[4]

A multivariate model was used to control for other factors. This model is an adaptation of the general model formulated by Albrecht et al. (1977) adapted in part by Baldwin (1984) and Brown, Richardson and Schwager (1987), for example, and endorsed by Brown, Foster and Noreen (1985, p. 125) and Foster (1986, p. 287). Albrecht et al. (1977) viewed FAF accuracy within a multivariate framework and suggested the following variables as potential determinants of FAF accuracy: (1) earnings variability, (2) corporate age, (3) corporate size, (4) detail of information, (5) corporation industry, (6) lead time to terminal date, (7) calendar year of forecast, and (8) forecaster. In addition to CS, this study considers factors (1), (2), (3), (4), (6) and (7) as potential determinants of EPS forecast accuracy.[5] Time series data from the quarterly industrial COMPUSTAT file (COMPUSTAT) are used to measure CS; FAF data from the Value Line Investment Survey (Value Line) are used to measure EPS forecast accuracy.

3.1 Hypothesis

The following null hypothesis (Alternative 3) was tested using multiple regression analysis.

H_0 There is no association between the degree of corporate seasonality and the quarterly income forecast errors of financial analysts.

3.2 General Model

The following general model was used:

FE = f(CS, PVAR, SIZE, TIME)

where

FE = EPS forecast error,

CS = Degree of corporate seasonality (DSS, DSE),

PVAR = Past year-to-year variability of earnings,

SIZE = Firm size, and

TIME = Number of days between forecast date (FDATE) and subsequent earnings announcement date (ADATE).

Since FAF accuracy varies across years (O'Brien, 1988) and CS effects on FAF accuracy could vary across years and quarters, regression models were estimated for every quarter represented in a seven-year FAF sample (1980-86). Since the same firms were used across years, joint generalized least squares (JGLS) was used to jointly estimate sets of regressions as systems of seemingly unrelated regressions (SUR). Zellner (1962) notes that gains in estimation efficiency can be achieved by using SUR, which takes into account the fact that cross-equation error terms may not be zero. In all, there were eight SUR estimations needed for this study (four quarterly systems, Q1-Q4, for each CS measure, DSS and DSE).

3.3 Variables

3.3.1 EPS Forecast Error. FE, the dependent variable, is the absolute value of the difference between forecasted EPS and actual EPS scaled by the absolute value of forecasted EPS. Expressed in percentage terms, this metric can be denoted as follows:

$$FE = (|(FEPS - AEPS) / FEPS|) \times 100$$

where FEPS = forecasted EPS, AEPS = actual EPS, and | | = absolute value operator. Values in excess of 300 percent were truncated at 300 percent.[6] Value Line was used to provide FEPS and AEPS data for the first, second, third and fourth quarters (Q1, Q2, Q3, Q4) of the current year. In effect, these four FAFs represented step-ahead-one (t+1) through step-ahead-four (t+4) forecasts. All data were adjusted for stock splits and stock dividends.

3.3.2 Corporate Seasonality. CS, the variable of interest, was measured both in terms of corporate sales (DSS) and corporate earnings (DSE). In this study, DSS and DSE are expressed in percentage terms. Each represents the relative contribution of the seasonal component (S) to the variance of the original series for span one, the interval between adjacent observations. The Census X-11 Model (Shiskin, Young and Musgrave, 1967) was used to compute these two measures for each year (1980-86) using a time window of the preceding ten years of COMPUSTAT data.

The X-11 Model, which is used to seasonally adjust a wide variety of economic time series, decomposes time-series data into three components: seasonal, trend-cycle, and irregular. The seasonal component reflects the intrayear variation which is repeated from year to year; the trend-cycle component reflects the long-term trend and the business cycle; the irregular component reflects the residual variation in the data. In this study, the additive formulation of the X-11 Model was used on both sales and earnings to ensure comparability between DSS and DSE and to accomodate negative earnings numbers which precluded using the multiplicative alternative. This additive decomposition can be represented as follows:

$$X = S + C + I$$

where X is the variable of interest (sales or earnings), S is the seasonal component, C is the trend-cycle component, and I is the irregular component.

In effect, then, DSS and DSE are summary measures of the relative contribution of S to the variability of each series (sales or earnings). Such measures are generated as standard outputs of the X-11 Model.[7] Since the expected sign of the association between CS and FE cannot be determined a priori (see Section 2), a two-tailed test is used for this variable.

3.3.3 Past Year-to-year Earnings Variability. PVAR represents past year-to-year earnings variability, which has been shown to affect FAF performance (Barefield and Comiskey, 1975; Pincus, 1983). It is measured using the Value Line Earnings Predictability Index (VLPI). To mitigate the effects of quarter-to-quarter seasonality and provide investors with a measure of past EPS variability, Value Line computes this index from the year-to-year standard deviation of the percentage change in the quarterly earnings series over the past five to ten years. This seasonality-free index is scaled from 5 to 100, such that 100 represents a highly predictable (low PVAR) company. Since the expected sign of VLPI is negative, a one-tailed test is used for this variable.

3.3.4 Firm Size. SIZE is measured as the natural log of the previous year's annual sales (LnSALES). This variable is included as a proxy for the amount of information made available by companies and the amount of effort expended by financial analysts in predicting corporate earnings. SALES is used as a proxy for size in the Fortune 500 and has been used as a proxy for size in various studies (e.g., Schiff, 1978). Brown, Richardson and Schwager (1987), Mendenhall and Nichols (1988), Bathke, Lorek and Willinger (1989) and others have found that EPS forecasts generally are more accurate for large firms than small firms. Since the expected sign of SIZE is negative, a one-tailed test is used for this variable.

3.3.5 Time Lag. TIME, the number of days between the FDATE and ADATE, is included to control for FAF performance differences due to the potential acquisition of new information by financial analysts subsequent to the publication of an EPS forecast. Crichfeld, Dyckman and Lakonishok (1978), Bamber (1987), O'Brien (1988) and others have observed that FAFs generally become more accurate as the earnings announcement date approaches. Since the expected sign of TIME is positive, a one-tailed test is used for this variable.

3.4 Data Sample

Every firm (1) was listed in both Value Line and COMPUSTAT, (2) was a December fiscal-year company throughout the sample period, (3) remained in its designated four-digit COMPUSTAT industry classification code throughout the sample period, (4) had complete COMPUSTAT quarterly sales and earnings before extraordinary items from 1970-I to 1985-IV, (5) had a complete set of Wall Street Journal EPS announcement dates, and (6) had no FE denominators (FEPS) between -.05 and .05. Criterion (6) was used to mitigate outliers due to small denominators (see Bamber, 1987). Satisfying these criteria were 174, 173, 183 and 193 firms with complete data for the first, second, third and fourth quarters (Q1, Q2, Q3, Q4), respectively.

In all, there were 197 different firms representing 46 two-digit, 83 three-digit, and 88 four-digit Standard Industrial Code (SIC) categories. Since each quarter required seven years of complete data for the JGLS analysis, there were 1,218, 1,211, 1,281, and 1,351 FAFs for quarters Q1 through Q4, respectively. Four data items were required for each FAF (FEPS, AEPS, FDATE, ADATE). In addition, for each firm in the 197-firm sample, there were three variables (DSS, DSE, SIZE) computed once for each year (Q1 through Q4) from COMPUSTAT data through the end of the preceding year and one variable (VLPI) recorded once for each year from Value Line on the date that the four quarterly FAFs were made. There were 1,379 individual measurements recorded for each of these four variables (197 firms x 7 years).

3.5 Regression Models

Two regression models were used to test for CS effects:

$$LFE_j = \beta_0 + \beta_1 DSS_j + \beta_2 VLPI_j + \beta_3 SIZE_j + \beta_4 TIME_j + \epsilon_j \qquad \text{(Model 1)}$$

$$LFE_j = \beta_0 + \beta_1 DSE_j + \beta_2 VLPI_j + \beta_3 SIZE_j + \beta_4 TIME_j + \epsilon_j \qquad \text{(Model 2)}$$

where LFE_j = LnFE for firm j, DSS_j = degree of seasonality in sales for firm j, DSE_j = degree of seasonality in earnings for firm j, $VLPI_j$ = Value Line earnings predictability index for firm j, $SIZE_j$ = LnSALES for firm j, and $TIME_j$ = ADATE - FDATE for firm j. Each variable on the right-hand side of these two cross-sectional models was measurable before the dependent variable became known on the earnings announcement date (ADATE).

Since FE tends to be skewed, LFE, the natural log transformation of FE, was used to satisfy the distributional assumptions of the two regression models. Also, since DSS and DSE tend to be highly correlated, these two measures were not both included in a single model to avoid multicollinearity problems.[8] Regression diagnostics indicated that (1) the models as specified did not violate the distributional assumptions of the regression analysis and (2) the independent variables that were included in each model did not exhibit multicollinearity problems.

4. Empirical Evidence

Empirical evidence on the association between CS (DSE and DSS) and FAF performance (LFE) is presented in this section. This evidence does not support the proposition that high CS tends to impair FAF performance (Alternative 2) nor does it support the proposition that high CS generally tends to improve FAF performance (Alternative 1).

4.1 Descriptive Statistics

Table 1 provides a seasonality profile of the sample. Based on the full 197-firm sample (i.e., every firm that was used in at least one quarter), it indicates that on average DSS is slightly higher than DSE (58.0 versus 55.9). It also identifies a number of industries with high CS (SIC 20, food and kindred products; SIC 27, printing and publishing; SIC 49, electric, gas and sanitary services) and low CS (SIC 10, metal mining; SIC 26, paper and allied products; SIC 48 communications). None of the two-digit SIC categories exceeded 10 percent of the full sample and only six two-digit SIC categories exceeded 5 percent of the full sample. Thus the composition of this sample is relatively diverse both in terms of seasonality and industry representation.

Table 2 provides some additional statistics on the four quarterly samples (Q1-Q4) used in the regression analysis. As expected, LFE and FE increased with TIME from 2.883 and 38.520 (Q1) to 3.248 and 51.032 (Q4), respectively. As indicated by the standard deviations and means of LFE versus FE and SIZE versus SALES, the log transformations of FE and SALES reduced the coefficients of variation associated with those variables.

4.2 Regression Results

DSS and DSE were used in cross-sectional regressions with LFE as the dependent variable and VLPI, SIZE, and TIME as other explanatory variables. These regressions were estimated jointly by quarter using JGLS. The results of these regressions indicate that CS generally did not affect FAF performance (Alternative 3).

Table 3 presents the regression results for Model 1 which includes DSS as an independent variable. Out of 28 cross-sectional tests, the regression coefficient for DSS was significant once in Q1 (1984), twice in Q3 (1982, 1986), and three times in Q4 (1982, 1984, 1986). The sign was positive once (in Q1) and negative five times (in Q3 and Q4). Using a one-tailed test ($\alpha <$ .10), VLPI was significant 28 times, SIZE was significant seven times and TIME was significant 13 times. The system R-squares ranged from .146 (Q3) to .206 (Q1).

Table 4 presents the regression results for Model 2 which includes DSE as an independent variable. These results are similar overall to the Model 1 results. Out of 28 cross-sectional tests, the regression coefficient for DSE was significant once in Q1 (1984), twice in Q3 (1982, 1983), and once in Q4 (1985). The sign was positive once (in Q1) and negative three times (in Q3 and Q4). Using a one-tailed test ($\alpha < .10$), VLPI was significant 28 times, SIZE was significant seven times, and TIME was significant 13 times. The system R-squares ranged from .146 (Q3) to .208 (Q1).

Overall, then, except for the first quarter of 1984, which indicated a statistically significant positive sign for both DSS and DSE, the results of the multiple regression analysis do not support the proposition that CS adversely affects FAF performance (Alternative 2). In addition, except for five DSS quarters (Q3:1982, Q3:1986, Q4:1982, Q4:1984, Q4:1986) and three DSE quarters (Q3:1982, Q3:1986, Q4:1985), the results do not support the proposition that CS improves FAF performance (Alternative 1). Consequently, the results generally indicate that the null hypothesis (Alternative 3) could not be rejected.

5. Conclusions

This study investigates the proposition that CS could either favorably or unfavorably affect FAF performance (measured in terms of forecast errors, FEs). Two potential CS-FE linkages were examined: (1) the association between DSS and EPS forecast accuracy and (2) the association between DSE and EPS forecast accuracy. In both cases, a multivariate approach was used to control for other potential determinants of EPS forecast accuracy.

The results indicate that except in one quarter (out of 28 quarters), on average FAF performance was not adversely affected by CS. Therefore, it appears that additional disclosures are not needed to remedy a positive association between CS and FE (Alternative 2). However, since CS represents pattern (which tends to improve forecast accuracy) and there generally was no negative association between CS and FE (Alternative 2), the results may also suggest that financial analysts are not exploiting this pattern very well. Perhaps, then, additional emphasis should be placed on the CS component and future research should be designed to address this issue further. Also, since the results (Alternative 3) could be due to a variety of factors, additional research is needed to determine why the net impact of CS on EPS forecast errors is essentially zero, and not negative as expected under Alternative 1.

By using a multivariate approach, the results also serve to enhance our general understanding of the joint determinants of EPS forecast accuracy. Knowledge of these determinants is useful for research requiring measures of the market's expectation of earnings (Brown, Richardson and Schwager, 1987, p. 50). Noteworthy is the impact on FAF performance of past year-to-year earnings variability, PVAR, as indicated by the <u>Value Line</u> earnings predictability index, VLPI. This index, which is based on past year-to-year earnings variability, was statistically significant in every cross-sectional regression. It appears, then, that even for forecasting on a quarter-to-quarter basis, the major source of inaccuracy in FAFs is year-to-year earnings volatility, rather than the extent of any seasonal patterns (which seem to be reasonably anticipated). Research designs which need to measure earnings surprise or control for ex ante predictive ability for some other reason therefore should consider controlling for PVAR, which affected FAF performance more often than SIZE or TIME. These results also suggest that future studies attempting to measure or control for SIZE effects should consider PVAR as a potential omitted variable.

FOOTNOTES

1. See Blough (1953), Capon (1955), Shillinglaw (1961), Green (1964), Taylor (1965), Rappaport (1966), Frank (1969), Backer (1970), Bollom and Weygandt (1972), Coates (1972), Edwards, Dominiak and Hedges (1972), Reilly, Morgenson, and West (1972), Bollom (1973), Kiger (1974), Nickerson, Pointer and Strawser (1975), Foster (1977), Carlson (1978), Schiff (1978), Leftwich, Watts and Zimmerman (1981), Fried and Livnat (1981), Maingot (1983), Bathke and Lorek (1984), and Burrowes (1986).

2. An examination of the most seasonal firms in the current sample (upper third) revealed no such disclosures. Seasonality was mentioned briefly by only 12.1 percent of these firms (eight cases) and not mentioned at all by 87.9 percent.

3. By comparing seasonal and nonseasonal models of quarterly data, Foster (1977) provided evidence which indicated that investors adjust for seasonality, but he did not examine the impact of seasonality on the accuracy of EPS forecasts published by financial analysts. Collins, Hopwood, and McKeown (1984) provided some initial evidence which indicated that seasonal firms might be associated with lower FAF errors than nonseasonal firms. However, because the focus of their study was not on seasonality per se, there were no controls for other determinants of FAF accuracy and no statistical tests were performed on the observed differences.

4. Previous studies concerned with measuring CS typically have relied on categorical measures derived from various sources (e.g., Frank (1969), Kiger (1974), Schiff (1978), Collins, Hopwood and McKeown (1984), Lorek and Bathke (1984), Bathke, Lorek and Willinger (1989)).

5. Factor (3) serves as a proxy for factors (2) and (4). Factor (5) was not included because CS and other variables are aligned with industry membership. Factor (7) is implicit in the design which treats each year separately. Factor (8) was not incorporated in design since Value Line data were used exclusively. In addition, number of lines of business and exchange listing were examined in a pilot study but dropped from further consideration when results indicated no effects.

6. The percentage of truncations was less than 2.26 percent (114 out of 5,061 observations). Influence diagnostics indicated that the results were not driven by these or any other observations.

7. Recently, Dugan, Gentry and Shriver (1985) suggested that such measures might provide insights within an auditing context.

8. Pearson product moment correlation coefficients were significant for DSS-DSE (averaged .626) and DSE-VLPI (averaged .382). All other pairings were insignificant.

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Table 1

Seasonality Profile of Sample

SIC	Industry	No. of Firms	Average DSS%	Average DSE%
20	Food and kindred products	8	78.6	79.2
27	Printing and publishing	14	76.0	77.3
49	Electric, gas, and santitary services	18	73.5	71.5
36	Electrical equipment and supplies	10	67.7	48.3
37	Transportation equipment	8	62.1	54.2
35	Machinery, except electrical	10	60.4	45.3
28	Chemicals and allied products	19	59.1	58.3
32	Stone, clay and glass products	8	56.0	55.3
10	Metal mining	5	45.5	25.4
26	Paper and allied products	10	38.4	40.0
48	Communications	5	27.4	46.3
	All other (35 2-digit codes)	82	52.6	52.8
	Total Sample	197	58.0	55.9

Table 2

Means and Standard Deviations of Variables (1980-86)

	Q1		Q2		Q3		Q4	
	Mean	(SD)	Mean	(SD)	Mean	(SD)	Mean	(SD)
LFE	2.883	(1.299)	2.914	(1.265)	3.042	(1.245)	3.248	(1.242)
DSS%	58.608	(26.261)	58.221	(26.479)	57.841	(26.145)	57.662	(26.261)
DSE%	57.551	(26.629)	56.812	(27.114)	56.040	(27.742)	56.168	(27.076)
VLPI	58.460	(26.959)	57.460	(27.038)	56.291	(27.232)	55.869	(27.799)
SIZE	6.947	(1.323)	6.959	(1.280)	6.945	(1.306)	6.905	(1.303)
TIME	71.945	(27.544)	162.621	(27.531)	253.960	(26.972)	360.698	(30.040)
FE%	38.520	(58.569)	38.288	(56.492)	42.172	(59.026)	51.032	(66.319)
SALES[a]	2.556	(4.889)	2.345	(3.750)	2.505	(4.786)	2.394	(4.618)
FDATE[b]	41.484	(26.852)	41.854	(26.620)	42.188	(26.289)	41.560	(26.509)
ADATE[b]	113.429	(8.044)	204.475	(7.833)	296.148	(8.149)	402.258	(14.626)
Firms	n = 174		n = 173		n = 183		n = 193	

[a] In $ billions
[b] Julian date

Note: LFE = Ln Forecast Error, DSS = Degree of Seasonality in Sales, DSE = Degree of Seasonality in Earnings, VLPI = Value Line Earnings Predictability Index, SIZE = LnSALES, TIME = ADATE - FDATE, FE = EPS Forecast Error, SALES = Annual Sales, FDATE = Forecast Date, ADATE = EPS Announcement Date.

Table 3

Regression Coefficients and Significance Levels: Model 1

$$LFE_j = \beta_0 + \beta_1 DSS_j + \beta_2 VLPI_j + \beta_3 SIZE_j + \beta_4 TIME_j + \epsilon_j$$

First Quarter (n = 174 per year; system R^2 = .206)

Year	Intercept	DSS	VLPI	SIZE	TIME
1980	3.2159 (.000)	.0021 (.513)	-.0208 (.000)	.0395 (.737)	.0069 (.011)
1981	4.1500 (.000)	.0049 (.107)	-.0200 (.000)	-.1857 (.001)	.0114 (.000)
1982	4.4022 (.000)	.0029 (.415)	-.0230 (.000)	-.0926 (.101)	.0056 (.048)
1983	4.0064 (.000)	-.0013 (.711)	-.0216 (.000)	-.0234 (.374)	.0064 (.031)
1984	4.1707 (.000)	.0066 (.022)[b]	-.0261 (.000)	-.0026 (.481)	-.0027 (.839)
1985	4.0328 (.000)	.0049 (.148)	-.0155 (.000)	-.1446 (.015)	.0077 (.009)
1986	4.4015 (.000)	-.0012 (.724)	-.0227 (.000)	-.0751 (.130)	.0048 (.062)

Second Quarter (n = 173 per year; system R^2 = .184)

Year	Intercept	DSS	VLPI	SIZE	TIME
1980	3.6021 (.000)	.0004 (.900)	-.0180 (.000)	.0339 (.717)	.0012 (.337)
1981	3.2582 (.000)	.0047 (.154)	-.0193 (.000)	-.0324 (.318)	.0035 (.138)
1982	4.3076 (.000)	-.0033 (.302)	-.0241 (.000)	-.0309 (.319)	.0042 (.086)
1983	4.9415 (.000)	-.0007 (.819)	-.0257 (.000)	-.0478 (.220)	-.0004 (.552)
1984	4.1632 (.000)	.0008 (.806)	-.0201 (.000)	-.0281 (.333)	-.0010 (.632)
1985	4.2559 (.000)	.0014 (.679)	-.0149 (.000)	-.0421 (.277)	-.0013 (.652)
1986	3.6835 (.000)	-.0031 (.387)	-.0263 (.000)	-.0566 (.224)	.0067 (.023)

Third Quarter (n = 183 per year; system R^2 = .146)

Year	Intercept	DSS	VLPI	SIZE	TIME
1980	2.4684 (.003)	.0044 (.163)	-.0184 (.000)	.0626 (.846)	.0029 (.157)
1981	3.4308 (.000)	-.0016 (.610)	-.0210 (.000)	.0146 (.593)	.0034 (.125)
1982	3.8710 (.000)	-.0084 (.006)[a]	-.0185 (.000)	.0137 (.587)	.0040 (.091)
1983	3.6073 (.000)	.0023 (.477)	-.0192 (.000)	-.0623 (.173)	.0031 (.166)
1984	5.9504 (.000)	-.0033 (.314)	-.0202 (.000)	-.0485 (.224)	-.0058 (.969)
1985	5.1044 (.000)	-.0006 (.858)	-.0143 (.000)	-.1025 (.055)	-.0012 (.652)
1986	4.5234 (.000)	-.0061 (.042)[b]	-.0155 (.000)	-.1536 (.006)	.0032 (.124)

Fourth Quarter (n = 193 per year; system R^2 = .167)

Year	Intercept	DSS	VLPI	SIZE	TIME
1980	3.7117 (.001)	.0031 (.341)	-.0152 (.000)	.0065 (.541)	-.0004 (.560)
1981	1.6066 (.101)	.0021 (.429)	-.0220 (.000)	.0633 (.875)	.0068 (.002)
1982	3.4301 (.001)	-.0052 (.073)[c]	-.0214 (.000)	.0136 (.591)	.0044 (.041)
1983	3.6626 (.001)	-.0020 (.512)	-.0200 (.000)	-.0711 (.124)	.0034 (.098)
1984	5.2396 (.000)	-.0056 (.066)[c]	-.0204 (.000)	-.1090 (.039)	.0002 (.476)
1985	4.3799 (.000)	-.0029 (.351)	-.0118 (.000)	-.1044 (.050)	.0013 (.308)
1986	4.2139 (.000)	-.0049 (.084)[c]	-.0191 (.000)	-.1047 (.036)	.0032 (.087)

[a] DSS significant at .01 level (two-tailed test)
[b] DSS significant at .05 level (two-tailed test)
[c] DSS significant at .10 level (two-tailed test)

Table 4

Regression Coefficients and Significance Levels: Model 2

$$LFE_j = \beta_0 + \beta_1 DSE_j + \beta_2 VLPI_j + \beta_3 SIZE_j + \beta_4 TIME_j + \epsilon_j$$

First Quarter (n = 174 per year; system R^2 = .208)

Year	Intercept	DSE	VLPI	SIZE	TIME
1980	3.3249 (.000)	.0002 (.957)	.0208 (.000)	.0416 (.746)	.0067 (.013)
1981	4.4347 (.000)	-.0005 (.870)	-.0197 (.000)	-.1827 (.002)	.0111 (.000)
1982	4.4783 (.000)	.0038 (.308)	-.0241 (.000)	-.1013 (.918)	.0056 (.049)
1983	3.9363 (.000)	-.0002 (.959)	-.0216 (.000)	-.0231 (.375)	.0064 (.031)
1984	4.2633 (.000)	.0095 (.001)[a]	-.0293 (.000)	-.0113 (.418)	-.0026 (.837)
1985	4.2935 (.000)	.0028 (.406)	-.0162 (.000)	-.1507 (.012)	.0071 (.014)
1986	4.3713 (.000)	-.0015 (.671)	-.0222 (.000)	-.0722 (.139)	.0047 (.067)

Second Quarter (n = 173 per year; system R^2 = .184)

Year	Intercept	DSE	VLPI	SIZE	TIME
1980	3.7298 (.000)	-.0035 (.274)	-.0166 (.000)	.0346 (.722)	.0012 (.326)
1981	3.4531 (.000)	.0030 (.402)	-.0204 (.000)	-.0341 (.310)	.0033 (.151)
1982	4.1508 (.000)	-.0023 (.488)	-.0234 (.000)	-.0268 (.342)	.0044 (.075)
1983	4.8940 (.000)	.0000 (.988)	-.0258 (.000)	-.0478 (.220)	-.0003 (.543)
1984	4.1346 (.000)	.0021 (.524)	-.0210 (.000)	-.0297 (.323)	-.0009 (.617)
1985	4.4817 (.000)	-.0015 (.672)	-.0140 (.000)	-.0457 (.260)	-.0018 (.707)
1986	3.6289 (.000)	-.0035 (.360)	-.0252 (.000)	-.0532 (.237)	.0065 (.027)

Third Quarter (n = 183 per year; system R^2 = .146)

Year	Intercept	DSE	VLPI	SIZE	TIME
1980	2.6467 (.001)	.0032 (.341)	-.0192 (.000)	.0659 (.858)	.0026 (.189)
1981	3.4031 (.000)	-.0020 (.541)	-.0204 (.000)	-.0129 (.418)	.0035 (.123)
1982	3.5925 (.000)	-.0081 (.013)[b]	-.0165 (.000)	.0296 (.682)	.0041 (.086)
1983	3.7163 (.000)	.0011 (.752)	-.0196 (.000)	-.0665 (.160)	.0031 (.162)
1984	5.8611 (.000)	-.0029 (.394)	-.0197 (.000)	-.0437 (.247)	-.0058 (.969)
1985	5.3525 (.000)	-.0040 (.213)	-.0130 (.000)	-.1040 (.051)	-.0017 (.713)
1986	4.4992 (.000)	-.0083 (.006)[a]	-.0134 (.000)	-.1411 (.009)	.0028 (.150)

Fourth Quarter (n = 193 per year; system R^2 = .164)

Year	Intercept	DSE	VLPI	SIZE	TIME
1980	3.8337 (.001)	.0020 (.566)	.0158 (.000)	.0070 (.544)	-.0005 (.572)
1981	1.7313 (.075)	.0001 (.973)	-.0221 (.000)	.0649 (.880)	.0068 (.002)
1982	3.2553 (.002)	-.0047 (.122)	-.0201 (.000)	.0243 (.658)	.0044 (.041)
1983	3.5433 (.001)	-.0006 (.837)	-.0204 (.000)	-.0711 (.125)	.0034 (.099)
1984	4.8960 (.000)	-.0014 (.653)	-.0206 (.000)	-.1038 (.048)	.0003 (.447)
1985	4.4369 (.000)	-.0057 (.065)[c]	-.0099 (.000)	-.1008 (.055)	.0012 (.322)
1986	3.9784 (.000)	-.0031 (.291)	-.0187 (.000)	-.0982 (.046)	.0033 (.080)

[a] DSE significant at .01 level (two-tailed test)
[b] DSE significant at .05 level (two-tailed test)
[c] DSE significant at .10 level (two-tailed test)