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Business Cycle Variation in Earnings Forecasts and Common Stock Returns[†]

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There is considerable evidence that common stock returns are predictable and that they vary over the business cycle. One way to assess whether this predictability is a result of the rational variation of risk premia, consistent with market efficiency, is to measure the expectations of market participants over the business cycle. If the time variation of returns is a result of market inefficiency, then the expectational errors of market participants should be predictable using the same variables that forecast future returns. In this paper we investigate whether one measure of expectations, analysts' forecasts of earnings, exhibit predictable biases.

We investigate the Value-Line forecasts of the annual earnings of firms on the Dow-Jones indices (industrial, transportation and utility) over the period 1960-1986, and find that the forecast errors are predictable using the same variables that forecast future returns. We find that analysts consistently overestimate future earnings in economic downturns and underestimate future earnings in economic expansions. In addition, we find that the analysts revise their forecasts in a predictable way so that the magnitude of the analysts' bias decreases as the end of the fiscal year approaches. Counter to some previous studies, we find that average forecast errors may be either positive or negative, depending on economic conditions.

To determine whether the expectational biases of the analysts are incorporated into market prices, we measure the share price reaction to analysts' forecast revisions. If the market is efficient there should be no price reaction to predictable revisions. We find that the market reacts positively to upward forecast revisions, but find only mixed evidence on the price reaction to the predictable component of these revisions.

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1 Introduction

This paper investigates the relation between earnings forecasts in the *Value Line Investment Survey*, actual earnings and stock returns for firms on the Dow Jones Indices in the post World War II period. Specifically, we explore the changing relationships of the variables over the business cycle.

The findings of this study are of interest for several reasons. First, numerous studies have documented that expected returns vary in a predictable way over the business cycle. Fama and French (1988b, 1990) and Keim and Stambaugh (1988) show that post-WWII returns are predictable using market dividend-to-price ratios and macroeconomic indicators. Chen (1991) shows that the forecast variables used in these studies are measures of past and future GNP growth, and Daniel and Torous (1991) show that future returns are predictable using stochastically detrended industrial production.

Generally, this return predictability is attributed to time varying risk premia over the business cycle. The aforementioned studies find that expected returns are low in expansions and high in recessions. The variation is consistent with models such as that proposed by Abel (1988) in which risk-premia are high when output is low and is expected to increase.

However, an alternative explanation is that this time-variation in returns is due to biases in investors' expectations. For example, such patterns in returns would result if investors formed their expectations of future economic growth by extrapolating past economic growth in the manner suggested by Lakonishok, Shleifer and Vishny (1993), or if investors overreacted to good and bad economic news in the manner suggested by DeBondt and Thaler (1985, 1987). Were this the case, then approaching the trough of a recession investors would irrationally believe that future economic activity and future firm profits would be very low. Consequently, common stock prices would be depressed. When the economy began to recover, as could have been predicted had the investors' forecasts taken account of all available information, prices would adjust upward. Thus, the econometrician would observe high returns around business cycle troughs, and similarly low returns around business cycle peaks.[1]

[1] Some support for this irrationality hypothesis is provided by Boudoukh, Richardson and Smith (1993), who show that around business cycle peaks, the expected return on the value-weighted index is reliably less than the risk-free rate. To the extent that the VW index is a good proxy the market portfolio, it is difficult to construct an asset pricing model which has this implication.

Of course, it is difficult, if not impossible, to distinguish between these two hypotheses without some direct measure of expectations.[2] However, such a measure of expectations is available in analysts' forecasts of firms' earnings. In this paper, we investigate whether these earnings forecasts are efficient.

What we mean by an efficient forecast is one that incorporates all available information.[3] That is, the analysts' forecast of the firm's time t earnings at time $t-1$ should be the expectation of earnings given all information available to the analysts at time $t-1$ (which we denote by Ω_{t-1}.)

$$F_{t-1,t} = E[\tilde{E}_t | \Omega_{t-1}]. \tag{1}$$

We define the *forecast error* as the actual earnings minus the forecasted earnings:

$$\tilde{FE}_{t-1,t} = \tilde{E}_t - F_{t-1,t}$$

If analysts forecasts are efficient, than the forecast error will be orthogonal to the information set Ω_{t-1}, and, using iterated expectations, to every element of Ω_{t-1}. For example, since $DEF_{t-1} \in \Omega_{t-1}$

$$E[\tilde{FE}_{t-1,t} | DEF_{t-1}] = E[\tilde{E}_t | DEF_{t-1}] - E[E[\tilde{E}_t | \Omega_{t-1}] | DEF_{t-1}] = 0 \tag{2}$$

This relationship says that if the analyst is efficiently forecasting earnings, his forecast error cannot be predicted by any publicly available information, such as the default spread. Whenever equation (2) is not satisfied, we can conclude that analysts are not taking all information into account in forming their expectations.

There are numerous empirical studies showing both that Value Line earnings forecasts reflect market information, and that their earnings forecasts contain information not available to the market at the time of the forecast. As evidence on the first point, Brown, Griffin, Hagerman and Zmijewski (1987) show that stock returns around an earnings announcement are positively correlated with the earnings surprise. On the second point, Mendenhall (1991)

[2] Macroeconomists have empirically investigated the issue of how investors' form their expectations using survey data such as the ASA-NBER survey of forecasters. See Zarnowitz (1984, 1985) and Keane and Runkle (1984, 1985).

[3] This is closely related to the concept of efficient markets (Fama(1970, 1991)), though the only way that analysts' earnings forecasts will be efficient is if the analysts are compensated based on the accuracy of their forecasts.

and Stickel (1991) shows that common stock returns are high around positive forecast revisions. This suggests that there is information in the analysts' forecasts which is not available to the market through other sources. Furthermore, Philbrick and Ricks (1991) show that the market response to a given magnitude earnings surprise is greater for the Value Line forecasts then for either the IBES and S&P forecasts, suggesting that the market may "pay more attention" to the Value Line forecasts. This is consistent with their finding that the Value Line forecasts are of higher accuracy than either the IBES or the S&P forecasts.

However, some evidence also suggests that analysts do not efficiently incorporate all publicly available information in forming their forecasts. First, Abarbanell (1991), Brown, Foster and Noreen (1985), Fried and Givoly (1982) and Stickel (1990) and O'Brien (1988) have shown that analysts consistently overestimate earnings.[4] Also, Mendenhall (1991), and Abarbanell (1991) and Abarbanell and Bernard (1992) show that analysts' forecasts of annual earnings "underreact" to the information contained in past years earnings and in quarterly earnings announcements, respectively. Finally, DeBondt and Thaler (1990) show that analysts overreact to past changes in earnings.

We investigate the question of whether analysts' forecasts of earnings efficiently incorporate information about the business cycle, with the goal of determining if analysts exhibit predictable biases associated with the business cycle. Since our data is not readily available in machine readable form, we must limit our sample to a relatively small number of firms. We elect to use the set of firms which make up the Dow Jones Industrial, Transportation and Utility averages for two reasons. First, though this is certainly not a representative sample, these firms are closely followed, which means that there should be a large amount of information available about these firms, and that the variance of the firm specific component of the analysts' forecasts for these firm should be small. Second, the earnings of these firms', since they are relatively large, probably are highly correlated with economic growth. This means that any systematic biases in forecasting future economic growth should be reflected in the analysts' forecasts of the earnings of these firms. These two factors should combine to make business cycle related biases relatively easy to detect in this sample, if they exist at all.

[4]However, these studies are all based primarily on relatively short sample periods, none using any data from before 1975. We find here, using data from 1960-1986, that this bias is not consistent.

Our tests find that analysts' forecasts errors are highly predictable: roughly 30-40% of the variance of the average forecast error is explained using the same *ex-ante* business cycle indicators which have predictive power for stock returns (Fama and French (1989)). However, we find the interesting pattern that analysts' forecasts errors are *pro-cyclical*, meaning that analysts strongly overestimate future earnings in economic downturns and underestimate future earnings in economic upturns, while stock-returns are *counter-cyclical.* Furthermore, as might be expected based on the direction of the forecast errors, we find that analysts generally revise forecasts downwards in recessions and upwards in expansions. Thus returns are high (or prices move upward) over the same periods in which analysts revise their forecasts downwards. This is an apparent contradiction, because prior research has shown that, in general, the market reacts negatively when the analysts revise their earnings forecasts downward, but here we see that over the same period in which forecasts are revised downward, return are higher than average.

The final question that we attempt to answer is whether the analysts' biases are incorporated into market prices. We do this by looking at returns on firms' common stock around the date on which Value-Line revises its forecasts. We break the forecast revision into predictable and unpredictable components, where the predictable component is the expected forecast revision based on *ex-ante* variables. If the market is efficient, then the forecast revision period return should not be a function of the predictable component of the forecast revision. If the market's bias is equally as strong as that of the analysts' then the coefficient will be the same for the expected and unexpected components of the forecast revision.

We find that a firms excess return around a forecast revision date is strongly positively related to the unexpected forecast revision, but we find that there is no significant relation between the return and the expected component of the forecast revision. However, the standard errors on this coefficient are large enough that we also cannot reject the hypothesis that the coefficients on the expected and unexpected components are equal. We are currently exploring ways of improving this test and of decreasing the standard error on this coefficient, so as to allow us to discriminate between these two hypotheses.

2 The Data

2.1 Annual Earnings Forecasts and Actual Annual Earnings

Annual earnings forecasts and actual annual earnings data were hand collected for the firms on the Dow Jones Industrial, Utility and Transportation Averages[5] from the *Value-Line Investment Surveys* for the fiscal years 1960 to 1986.[6] The reason for this selection of firms is discussed in the introduction. The Value-Line forecasts are published weekly; a different set of stocks is covered each week for about 13 weeks (one quarter) before coverage returns to the same companies. There were generally four forecasts per year per firm (one forecast per quarter). Actual earnings are taken from Value-Line rather than from some other source such as COMPUSTAT to insure that the same measure of earnings is used for both the forecast and the actual earnings.[7]

We insured that forecasts and actual earnings were reported on the same split-adjusted basis using the following method. First, for each firm in the forecast database split dates were determined using data from the Center for Research in Security Prices (*CRSP*). For each split, Value-Line forecasts were inspected to determine precisely when Value-Line made the split-adjustment in their forecasts. This date was found to not always be equal to the CRSP reported split date. If the Value-Line split date was different that the actual split date (from *CRSP*), the Value-Line forecast and earnings were adjusted appropriately. Cumulative split factors (again, from *CRSP*) were retained for each firm to allow comparisons across time of forecasts and earnings.

The forecast errors were calculated by subtracting the forecasts from the (split-adjusted) actual earnings. Because the forecast-error variance is larger for firms with higher share value, and our statistical analysis assumes homoskedasticity, we normalize the forecast errors by dividing by the share-price on the day the forecast is made. [8]

[5]See the appendix for a listing of these firms

[6]We are currently collecting the data from 1986 to the present.

[7]Philbrick and Ricks (1991) discuss the earnings that are being forecasted by Value-Line, and the importance of matching Value-Line's forecasts to their actuals.

[8]As a check of robustness, we also repeated our analyses with un-normalized data, and after normalizing the data using the absolute value of the reported earnings-per-share. Our results were robust to the choice of normalization method.

2.2 Macroeconomic and Business Cycle Variables

As measures of the state of the economy we used the Dividend Yield on the CRSP value-weighted index ($DP(t)$), the term-spread ($TERM(t)$) and the default-spread ($DEF(t)$) as macroeconomic indicators. Fama and French (1998b, 1989) show that these variables are strongly correlated with the state of the economy and that they have considerable power to forecast future excess returns. ($DP(t)$ is defined as the sum of the dividends paid on the index over the past year divided by the price of the index at time t.[9] $TERM(t)$ is the difference between the time t yield on on the Ibbotson Aaa bond portfolio and the one-month t-bill yield, taken from the CRSP RISKFREE file. $DEF(t)$ is the difference in time t yield of the Ibbotson portfolio of 100 corporate bonds, and the yield on the Aaa bond portfolio.[10] These definitions are equivalent to those in Fama and French (1989). Chen (1991), and Daniel and Torous (1991) also show that these variables are indicators of past and future output growth.

In addition to the variables above we look at the relation of forecast errors to the annual log changes in industrial production, taken from CITIBASE.

2.3 Stock Price and Return Data

We use daily and monthly stock prices and returns supplied by CRSP. Monthly stock returns are available for the entire sample period. Daily prices and returns for the NYSE/AMEX firms we are interested in are only available after July 1962. The risk free rate is the one month T-Bill yield and is taken from the CRSP RISKFREE file.

3 Results

Table 1 provides summary statistics for the variables used in the study, broken down into five year periods. $FE(1)$ through $FE(4)$ denote the forecast errors, normalized by share price, for first, second, third and fourth quarter forecasts. An interesting result here is that the mean forecast error for is positive for four of the five time-periods examined for forecasts made in quarters 2-4. This suggests that previous work suggesting that analysts are generally optimistic may be specific to the sample period in these studies, which generally used data from the late

[9] Using annual dividends eliminates any seasonal present in the dividend data. The details of our method of calculating DP are given in the Appendix.

[10] Our thanks to Roger Ibbotson for supplying us with these data.

Table 1: Summary Statistics for Forecast Errors and State Variables (1960-1986)

	1960-1965		1966-1970		1971-1975		1976-1980		1981-1986	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
FE (1)	-0.001	0.02	0.002	0.014	0.009	0.019	0.011	0.026	-0.025	0.104
FE (2)	0.0008	0.018	0.003	0.011	0.007	0.015	0.010	0.024	-0.008	0.054
FE (3)	0.002	0.016	0.002	0.009	0.004	0.013	0.004	0.029	-0.004	0.030
FE (4)	0.005	0.014	0.004	0.011	0.003	0.007	0.003	0.016	-0.002	0.019
DEF	0.004	0.001	0.0038	0.001	0.0035	0.002	0.0038	0.001	0.006	0.0008
DP	0.032	0.003	0.030	0.002	0.033	0.006	0.045	0.005	0.046	0.007
$TERM$	0.016	0.006	0.007	0.005	0.019	0.015	0.020	0.016	0.022	0.019
ΔIP	0.042	0.047	0.061	0.028	0.029	0.053	0.032	0.072	0.019	0.064
ΔEPS	.	.	0.485	0.727	0.105	0.436	0.572	1.282	0.349	2.930

70's and 80's. Note that this table also shows that both the means and the standard deviations of the forecast errors decrease as the forecast date approaches the end of the fiscal year, as we would expect to see.

Table 2 gives the Pearson correlations for the variables used in the study. As expected, we find significant positive correlations between DEF, $TERM$ and DP. Further, these variables are negatively associated with the log of past and future production growth, ΔIP_t and ΔIP_{t+4} respectively. Interestingly, only the variables DEF and $TERM$ are significantly correlated with subsequent forecast errors, FE.

3.1 Evidence on the predictability of stock returns

Fama and French (1989) show that the default spread (DEF), the term spread (TERM) and the dividend yield on the value-weighted portfolio of NYSE stocks (DP) have power to forecast future stock returns. They show that DEF, TERM, and DP are countercyclical (that is high near business cycle troughs and low near peaks), and that these variables reliably forecast future returns on the CRSP value weighted (VW) and equal weighted (EW) indices as well as on a set of bond portfolios. TERM is shown to have power to forecast monthly and quarterly returns, and DEF has power to forecast 2-4 year horizon returns. Moreover, DEF and DP are shown to forecast roughly the same component of future returns.

We find that there is a close relationship between these variables ability to forecast returns

Table 2: Pearson Correlations for Analyst Forecast Errors and State Variables: 1960-1986 (p-values in Parentheses)

	FE_t	DEF_t	DP_t	$TERM_t$	ΔIP_t
DEF_t	-0.14				
	(0.0001)				
DP_t	-0.01	0.474			
	(0.47)	(0.0001)			
$TERM_t$	-0.15	0.20	0.03		
	(0.0001)	(0.0001)	(0.101)		
ΔIP_t	0.04	-0.47	-0.189	-0.23	
	(0.04)	(0.0001)	(0.0001)	(0.0001)	
ΔIP_{t+4}	-0.005	-0.13	-0.149	0.514	-0.143
	(0.847)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

and their ability to forecast errors in analysts' forecasts. As we show in Section 3.3, all three variables have power to predict forecast errors. In addition, we find that DP and DEF appear to be forecasting the same component of analysts' forecast errors, but we find that DEF does a better job of forecasting forecast errors than does DP. Interestingly, the evidence in Section 3.4 also suggests that while TERM only predicts revisions one quarter ahead, DEF predicts analysts' revisions several quarters out.

3.1.1 The relationship of the business cycle indicators to production growth

Chen (1991) shows that the same variables that predict returns in Fama and French (1989) are also strong indicators of past and future production growth. Specifically, he shows that DEF and DP are significantly *negatively* correlated with past and contemporaneous quarterly growth rates of GNP, as well as the growth rate one quarter ahead. In addition Daniel and Torous (1995) show that, while DEF is uncorrelated with future production growth rates, it has strong predictive power for production volatility several years into the future. TERM is *positively* correlated with both contemporaneous and future growth rate of GNP up to five quarters ahead.

3.2 The relationship between earnings and economic growth

To quantify the relationship between earnings and economic conditions for our set of firms, we regressed the average log earnings growth of the firms in our sample on present, past and future log changes in industrial production. These results are reported below (T-statistics are in parentheses):

$$\Delta EPS_t = \underset{(0.95)}{0.018} - \underset{(0.26)}{0.054}\ \Delta IP_{t-2} - \underset{(-2.69)}{0.559}\ \Delta IP_{t-1} + \underset{(4.02)}{0.823}\ \Delta IP_t - \underset{(-2.03)}{0.44}\ \Delta IP_{t+1}$$

Here ΔEPS_t is the average log growth in earnings for our sample from year $t-1$ to year t, and ΔIP_t is the log growth of industrial production from $t-1$ to t. The R^2_{adj} for this regression was 0.47. We use growth rates rather then levels here because of the possibility that earnings and industrial production may be integrated variables. With annual growth rates in industrial production, seasonality is not a concern.

These results show that this year's growth in earnings is strongly positively related to this year's growth in industrial production, and is negatively related both to last year's growth in industrial production and to next years growth in industrial production. This suggests that the relationship between earnings and industrial production is that the *level* of earnings is high when the *growth* in industrial production is high.

3.3 The predictability of analysts' forecasts

Table 3 reports the result of regressing subsequent (price-normalized) forecast errors on the state variables discussed in Section 2.2 and on the previous year's earnings change ($\Delta EPS_{t-12,t}$). Abarbanell and Bernard (1992) have shown that the previous year's earnings change has power to predict Value-Line analysts forecast errors. The results show that only DEF and $TERM$ are significantly associated with subsequent forecast errors in all four quarters; the coefficient on the previous year's earnings change is significantly positively only in the second quarter. Interestingly, the coefficients on DEF and $TERM$ are negative, suggesting that analysts' forecasts consistently overestimate future earnings in economic downturns and underestimate future earnings in economic expansions. These results, while supporting the idea that analysts are not efficiently using information about the business cycle, run contrary to the over-reaction hypothesis that analysts are pessimistic in recessions and optimistic in expansions.

Table 3: Regressions Relating Individual Analyst Forecast Errors to State Variables (1960-1986)

$$FE_{it} = \alpha + \beta(\text{StateVariables})_{t-1} + \epsilon_{it}$$

Quarter	State Variable Coefficients						R^2_{adj}	N
	$\hat{\alpha}$	DEF_{t-1}	DP_{t-1}	$TERM_{t-1}$	$\Delta IP_{t-12,t}$	$\Delta EPS_{t-12,t}$		
(1)	0.009	-4.27	0.08	-0.16	0.014	0.0003	0.06	782
	(1.69)	(-4.78)	(0.563)	(-2.47)	(0.59)	(0.56)		
(2)	0.01	-3.94	0.11	-0.16	0.007	0.001	0.07	902
	(2.4)	(-5.47)	(1.056)	(-2.92)	(0.44)	(1.98)		
(3)	0.01	-2.26	-0.13	-0.13	-0.01	-0.0001	0.03	931
	(3.14)	(-3.82)	(-1.38)	(-2.58)	(-0.92)	(-0.36)		
(4)	0.01	-1.65	-0.05	-0.14	-0.006	-0.0000	0.05	956
	(3.37)	(-3.81)	(-0.76)	(-3.74)	(-0.50)	(-0.23)		
(all)	0.009	-2.44	-0.02	-0.15	0.004	0.0002	0.05	3574
	(4.47)	(-7.85)	(-0.32)	(-5.96)	(0.49)	(0.63)		

Table 4 shows the results of regressing analysts' forecast errors on the macroeconomic variables. The t-statistics presented in Table 3 are likely to be overstated on account of cross-sectional correlation between forecast errors. Table 4, therefore, shows the results of regressing the quarterly mean analysts' forecast error on the macroeconomic variables. As a check of robustness, the regressions were run for price-deflated, absolute EPS deflated, undeflated forecast errors. The results are seen to be qualitatively similar for all deflators. The table only shows results of the regression using DEF, $TERM$ and DP as independent variables. In all three panels, in univariate and multivariate regressions, the coefficients on DEF and $TERM$ are negative and significant. The coefficient on DP is significant, however, only in the univariate regression; specifically, it loses explanatory power when DEF is in included in the regression.

Because analysts' forecasts get more accurate as the earnings announcement approaches, their forecast errors are not likely to be $i.i.d.$ each quarter. Table 5 presents quarter-by-quarter regression results of business cycle variables on the monthly mean forecast errors. The results confirm that the default spread is significantly associated with the mean forecast error in each quarter. Further, the magnitude of the coefficient decreases as the earnings announcement

Table 4: Results of regressions of aggregate forecast error on macroeconomic variables

Price Deflator

Regression	Intercept	TERM	DEF	DP	R^2_{adj}
(1)	0.0004	-1.1986			0.1431
	(0.06)	(-4.13)			
(2)	0.0466		-15.3635		0.3379
	(4.49)		(-7.07)		
(3)	0.0388			-1.5709	0.0947
	(2.06)			(-3.32)	
(4)	0.0457		-15.4684	0.0345	0.3309
	(2.82)		(-5.88)	(0.07)	
(5)	0.0535	-0.7796	-13.6273		0.3920
	(5.24)	(-3.08)	(-6.32)		

|EPS| Deflator

Regression	Intercept	TERM	DEF	DP	R^2_{adj}
(1)	-0.1630	-11.7821			0.1247
	(-2.24)	(-3.83)			
(2)	0.2439		-140.4607		0.2548
	(2.11)		(-5.82)		
(3)	0.2928			-17.4593	0.1079
	(1.50)			(-3.55)	
(4)	0.3499		-127.9245	-4.1785	0.2516
	(1.95)		(-4.39)	(-0.77)	
(5)	0.3145	-8.0116	-122.6190		0.3057
	(2.75)	(-2.82)	(-5.08)		

Un-normalized Forecast Errors

Regression	Intercept	TERM	DEF	DP	R^2_{adj}
(1)	-0.0766	-31.8481			0.0794
	(-0.31)	(-3.05)			
(2)	1.3260		-447.3737		0.2345
	(3.42)		(-5.52)		
(3)	0.2916			-24.9130	0.0114
	(0.43)			(-1.45)	
(4)	0.5330		-541.1959	31.2725	0.2505
	(0.89)		(-5.60)	(1.74)	
(5)	1.4971	-19.4212	-404.1229		0.2579
	(3.82)	(-2.00)	(-4.88)		

Table 5: Regression of Forecast Errors on Business Cycle Variables - Quarter by Quarter Regressions

	qtr 1	qtr 2	qtr 3	qtr 4
Intercept	0.093382	0.081965	0.06017	0.02022
	(3.32)	(4.23)	(3.64)	(1.76)
TERM	-0.914581	-0.705328	-0.474148	-0.48673
	(-1.51)	(-1.45)	(-1.20)	(-1.59)
DEF	-26.644793	-22.654828	-17.08013	-4.282512
	(-4.32)	(-5.82)	(-4.59)	(-1.90)

approaches. This is to be expected: later in the fiscal year considerably more information is available to the analyst, including the quarterly earnings from earlier in that year. The coefficient on $TERM$ also decreases and is marginally significant.

The forecast errors and *ex-ante* predicted forecast errors are also plotted in Figure 1 in both a time series plot and a scatterplot. These plots dramatically illustrate the degree of predictability of the forecast errors. Also, the plots, the scatterplot in particular, suggest that there are periods when the predicted forecast error is positive. This suggests that previous evidence that analysts' forecasts are on-average optimistic may be due to the sample period used in these studies.

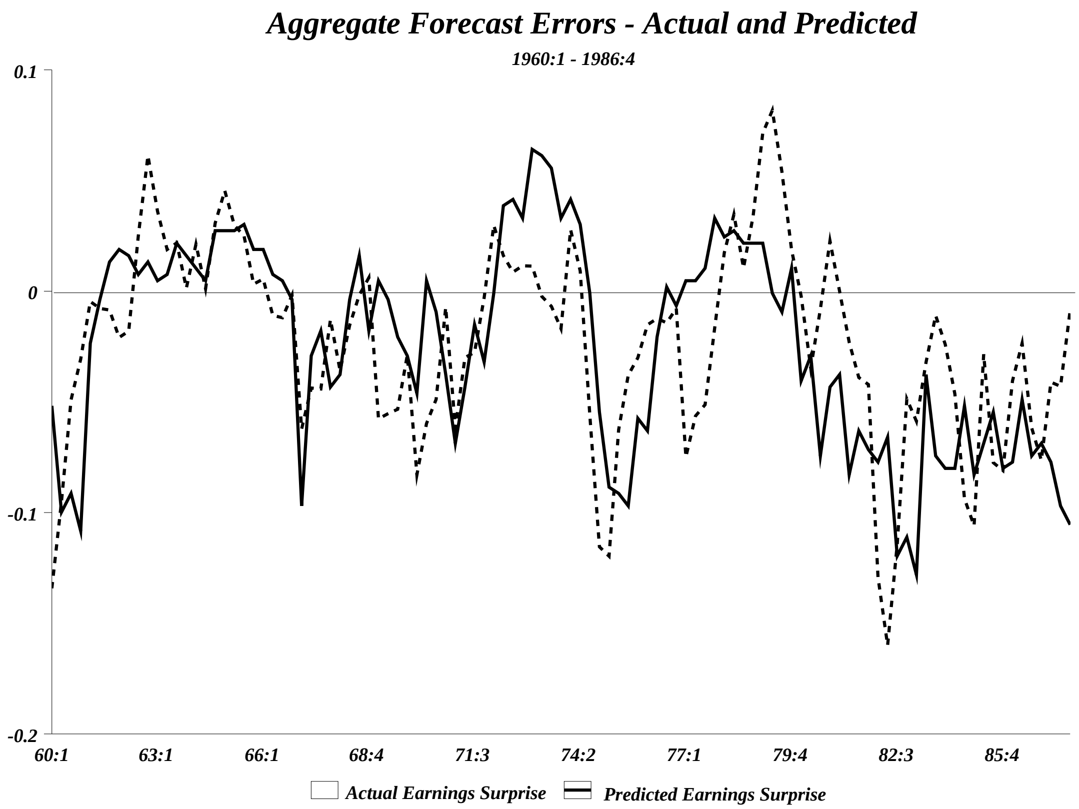
3.4 The predictability of analysts' forecast revisions

Table 6 presents the results of regressing the analysts' forecast revisions on the business cycle indicators. The forecast revision is defined as

$$FR_{i,y,q} = \frac{F_{i,y,q} - F_{i,y,q-1}}{P_{i,y-1}},$$

where $F_{i,y,q}$ now denotes the q'th quarter forecast of year y earnings for firm i, and $P_{i,y-1}$ denotes the share price and the end of year $y-1$. For example, the second quarter forecast revision for 1987 is calculated by subtracting the first quarter forecast of 1987 earnings from the second quarter forecast of 1987 earnings and dividing by the price of the stock on the last trading day of December 1986. In the last row of the Table (labeled $e.a.$ for earnings announcement) the dependent variable is the difference between the announced year y earnings and the fourth quarter forecast of these earnings (divided by the beginning of the year price).

Figure 1: Forecast Errors and *ex-ante* predicted forecast errors using the default spread



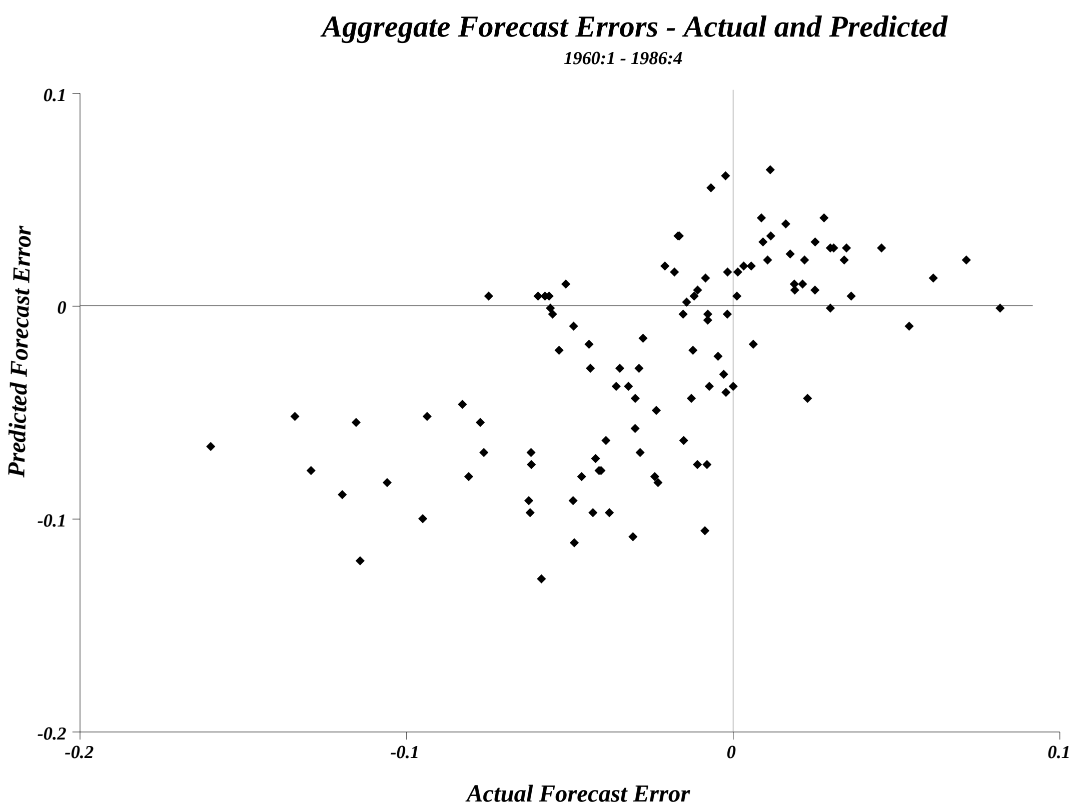


Table 6: Regressions of Analyst Forecast Revisions on State Variables (1960-1986)

$$FR_{i,q,y} = \alpha + \beta_1 DEF_{y-1} + \beta_2 TERM_{y-1} + \epsilon_{i,q,t}$$

Quarter	State Variable Coefficients $\hat{\alpha}$	DEF_{t-1}	$TERM_{t-1}$	R^2_{adj}
2	0.0048	-1.373	-0.052	0.037
	(4.634)	(-5.471)	(-2.12)	
3	0.0045	-1.301	-0.023	0.027
	(4.579)	(-5.485)	(-1.045)	
4	0.0013	-0.755	-0.013	0.009
	(1.431)	(-3.299)	(-0.6005)	
e.a.	0.0028	-0.935	-0.012	0.005
	(1.930)	(-2.641)	(-0.351)	

The dependent variables are in all cases based on yields at the end of the preceding year.

From Table 6 we see that forecast revisions are highly predictable, and all predictable revisions are opposite the direction of the bias; analysts do fix their (predictable) mistakes over time in a predictable way. DEF_{t-1} is significant predictor of all three forecast revisions, but $TERM_{t-1}$ only has power to predict the one-quarter ahead forecast revision. In addition, the final earnings surprise (*i.e.,* the difference in the fourth quarter forecast and the announced earnings) is predictable using the default spread from the end of the preceding year.

These results are particularly interesting in light of the fact that Fama and French (1989) and Chen (1991) find that TERM has power to forecast future stock returns over relatively short horizons of a month or a quarter, while DEF has power to forecast returns out several years.

3.5 The Market reaction to predictable forecast revisions

The "anomaly" that we have found is that analysts' forecasts strongly overestimate earnings just when expected returns are high. This means that, if at some point in time the default spread and the term spread are high, one can predict both that the analysts will revise downward their earnings forecasts over the next year and that the earnings which are eventually reported will be less than what the analyst has predicted. Based on these same state variables we know that the market return over the next year should be higher than average, as discussed in Section 3.1. This is an apparent contradiction, as numerous studies have shown that the market will tend to react negatively both when the analysts revise their forecasts downward, and when the earnings surprise is negative.

Based on the literature on overreaction (*e.g.* DeBondt and Thaler (1985,1987) and Chopra, Lakonishok and Ritter (1992)), one might have anticipated the opposite result, that analysts overreact to a decline in GNP, and hence would be overly pessimistic in recessions and optimistic in expansions. This would have provided a potential explanation of why there is so much variation in returns over the business cycle – that you have high returns coming out of a recession because the market is "surprised" when the economy and earnings recover after a downturn. But what we have instead found is very strong evidence that analysts tilt their forecasts in the other direction.

The result we have obtained indicates that biases in analysts forecasts cannot explain the large variation in returns over the business cycle. Perhaps the market is efficiently using the analysts' forecasts, and therefore not reacting to the predictable component of subsequent forecast revisions and earnings surprises. Alternatively, the market might have indeed react to these events, which would mean that, exclusive of the forecast revision dates and earnings revision dates, expected returns are even more volatile than previously thought.

To investigate whether the market makes the same expectational errors the analysts do, we split the analysts' forecast revisions up into two components: the expected and unexpected revisions. The idea here is that we can determine, based on the *ex-ante* DEF and TERM how much an analyst is likely to revise his forecasts over the next quarter, assuming a linear relationship. This amount is the predicted forecast revision. The difference between the actual and predicted forecast revision is then defined as the unpredictable component of the forecast revision.

The market should, on average, react to the unexpected forecast revisions, meaning that that the firms' stock price should move in the direction of the earnings forecast revision. However, if the market is efficient, then when an analyst revises his forecast by the predicted amount there should be no market reaction

To determine the predicted forecast revisions we regress the forecast revisions on the *ex-ante*

DEF and TERM:

$$\tilde{FR}_t = \underset{(7.68)}{0.0048} \underset{(-8.89)}{-1.245 \cdot DEF_{t-1}} \underset{(-3.33)}{-0.0495 \cdot TERM_{t-1}} + u_t \tag{3}$$

where here FR_t is defined to be the value of the first earnings forecast subsequent to time t forecast minus the time t forecast, divided by the share price at the end of the month preceding the time t forecast. DEF_{t-1} and $TERM_{t-1}$ are the default spread and term spread values from the beginning of the month preceding the month the forecast is made. This means that there is always at least one month between the day DEF_{t-1} and $TERM_{t-1}$ are calculated and the day the earnings forecast is released. Value Line claims that their forecasts are made no later than 9 days prior to the Value Line report date, so this procedure should insure that these data will become available to the analyst prior to the time t forecast and *not* during the period between the two forecasts.

Based this we define the predicted forecast revision PFR_t as simply the fitted value of the regression in equation (3):

$$P\hat{F}R_t = \hat{\alpha} + \hat{\beta}_1 DEF_{t-1} + \hat{\beta}_2 TERM_{t-1}$$

and the unpredictable component of the forecast revision UPR_t as the difference between the actual forecast revision and the predicted component, which is just the residual of the regression in equation (3):

$$U\hat{P}R_t = \tilde{FR}_t - PFR_t = \tilde{u}_t.$$

Then, to determine the market reaction to predicted and unpredictable components of the forecast revision we regress the excess returns (net of the return on the value-weighted index) around time of the release of the second forecast on the predicted and unpredictable forecast revisions:

$$\tilde{R}_{i,t} - \tilde{R}_{VW,t} = \alpha + \beta_1 U\hat{F}R_t + \beta_2 P\hat{F}R_t + \tilde{\epsilon}_t$$

We perform these regressions for a set of return windows around the second forecast report date. The results of these regressions are reported in Table 7. For example, where the *Window* column reads "5 to 14", this means that the return from 5 days after to 14 days after the Value Line report date was regressed on the UFR and PFR.

We see that the coefficient on UFR is strong for windows from 35 days before the report data to 14 days after the report date. That the coefficients are large well before the report date is not a surprise: if good (bad) information arrives during the forecast revision period, the return and the unexpected forecast revision are both likely to be positive (negative).

The fact that the UFR coefficient is positive for the -5 to 4 and 5 to 14 window indicates that the market is paying attention to the information contained in the Value Line forecast: when the unexpected forecast revision is positive, the market interprets this as a strong signal and the stock price increases. Note that the market reaction is strong over the 5 to 14 day window, but is insignificant after 15 days after the report date. Value Line claims that the report is in the subscribers hands *on* the report date, so it is surprising to see such a significant response coefficient for the 5 to 14 day window.

The coefficient for the predictable component of the forecast revision is always insignificant. However, this cannot necessarily be interpreted as evidence that the market does not incorporate the analysts' biases. The problem is that the standard errors on the coefficients of PFR are so large that it is impossible to reject either the hypothesis that $\beta_2 = 0$ or the hypothesis that $\beta_2 = \beta_1$, that is that the market is equally as biased as the analysts.

We are currently exploring ways of improving our ability to assess the markets' reaction to the analysts predictable forecast revision. Our hope is that some improved methods that we are exploring will allow us to discriminate between the two hypotheses discussed above.

4 Conclusions

We have shown that the same set of variables that predict stock returns also predict analysts' forecast errors. However, the direction of these two effects appears contradictory. We have shown that analysts' year-ahead forecasts of earnings are over-optimistic in recessions, when past economic growth has been poor, and are pessimistic in expansions, when past economic growth has been high. We have also shown that analysts, on average, later revise their forecasts downward in recessions and upward in expansions, but that even their end-of-the year forecasts do not eliminate this business cycle related bias. In contrast to the direction of the forecast revisions, stock returns are countercyclical: high in recessions and low in expansions. This means that stock returns are high (low) over the same years in which analysts revise their

Table 7: Results of regressing firm returns around forecast revisions on predicted and unpredicted forecast revisions. (T-Statistics in parentheses)

Window	Intercept	UFR_t	PFR_t
-35 to -26	0.000251 (0.332)	0.392678 (4.616)	0.967755 (1.294)
-25 to -16	-0.0002 (-0.227)	0.189796 (2.187)	0.731595 (1.188)
-15 to -6	-0.0009 (-1.191)	0.36814 (4.17)	-1.107099 (-1.631)
-5 to 4	-0.0004757 (-0.676)	0.255359 (3.044)	-0.188542 (-0.298)
5 to 14	-0.0025 (-3.17)	0.264993 (3.14)	-0.516354 (-0.769)
15 to 24	-0.00122 (-1.584)	0.082515 (0.96)	-1.149022 (-1.616)
25 to 34	.0001 (0.075)	0.142388 (1.641)	0.290104 (0.447)

forecasts downward (upward), and are high over years in which analysts are “surprised” by lower than expected earnings.

We attempted to analyze whether the market incorporates the biases of the analysts by investigating the market’s reaction to unexpected and expected forecast revisions. We find that the market reacts strongly to unexpected forecast revisions, suggesting that these contain information not already incorporated into prices. While we find no evidence that the market reacts to expected forecast revisions, the standard errors on our estimates of these response coefficients of the same order as the coefficients on the market response to the unexpected forecast revisions. This means that if the market reacts to the expected forecast revision in the same way that it reacts to the unexpected forecast revision, we would still conclude that the coefficient was not significantly different from zero.

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