CORPORATE EARNINGS FORECASTS AND THE MACROECONOMY

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Abstract:

Analyst forecast errors contain time-period-specific commonalities, indicating that they are not independent observations across firms. This paper explores macroeconomic explanations for the common time-period-specific component of analyst forecast errors, using data from the period 1976 - 1988. The main results are: (1) macroeconomic news about industrial production, inflation, interest rate changes and market returns that arrives during the year explains a significant portion of the time variation in corporate earnings, (2) macroeconomic news that arrives after analysts have made current-year earnings forecasts is reflected in their forecast errors, and (3) in spite of this, controlling for the effects of macroeconomic news does not alter the fact that analysts significantly overestimate earnings on average.

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1. Introduction

It is well-known that corporate earnings, like corporate stock returns, tend to move together because of macroeconomic and industry-wide events that affect many firms in similar ways.[1] It is less well-understood what specific economic events and forces shape this co-movement. Analyst forecast errors likewise exhibit co-movement through time, especially when the forecasts were generated over moderate to long time horizons. Because analysts update their corporate earnings forecasts to incorporate new information arriving throughout the year, earnings forecasts become more accurate, on average, as the year end approaches. Putting togther these two phenomena, earnings co-movement and analyst updating, implies that longer-horizon forecast errors should reflect common shocks, or macroeconomic news that arrived after the forecasts were made. This paper sheds light on the macroeconomic events that affect corporate earnings and are reflected in the significant cross-sectional covariation of forecast errors.

Early investigations of macroeconomic influences on earnings used aggregate earnings indices, analogous to market index models of common stock behavior. Brown and Ball (1967) found that an economy-wide earnings index accounted for 35 to 40% of the cross-sectional variation in individual firms' earnings, and an additional 10 to 15% was explained by industry indices. Gonedes (1973) tested a wide variety of index models and concluded that a market index model was the most "descriptively valid," and that industry influences were not important. In contrast, Magee (1974) found "industry-wide commonalities...are no less significant than

[1] E.g., Brown and Ball (1967), Gonedes (1973), Magee (1974).

economy-wide commonalities in explaining changes in firms' earnings numbers," again using index models.

The importance of these information-based commonalities for forecasting is illustrated in Table 1, which shows statistical evidence that a time-period-specific component to forecast errors is increasingly important as the forecasting horizon becomes longer. I examine median analyst forecasts available on the IBES Summary tape at three times during the year, namely one, six and eleven months prior to the fiscal year end month.[2] To illustrate the time-period-specific phenomenon, I align horizons in calendar time, and perform the analysis separately on each of four fiscal year ends. Table 1 is based on a regression of forecast errors on year dummy variables, to capture time-period-specific common information in forecast errors.[3] The F statistics test whether the average forecast error varies significantly from year to year. These statistics increase monotonically in magnitude and statistical significance with the forecast horizon, indicating that year-to-year differences are more important over longer forecasting spans than over short spans. Similarly, the regression R^2 numbers increase with the horizon, indicating that a greater proportion of forecast error variance is explained by year-specific information over long horizons than over short horizons. These results, while not surprising, are evidence that common shocks are reflected in the cross-section of earnings forecast errors. Forecast errors reflect information that was not anticipated by the forecaster, and longer horizons allow more time for unanticipated events to affect the outcome.[4]

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[2]The sample and data sources are described in more detail in section 2 of the paper.

[3]Because there may be strong industry associations with some fiscal yearends, I repeated this analysis in a model with both year and industry dummy variables. None of the results discussed here are materially affected.

[4]O'Brien (1988) contains a similar result, for forecast horizons varying between 5 and 240 trading days prior to the earnings announcement. Elton, Gruber and Gultekin (1984) fail to find a strong economy-wide influence when they decompose analyst mean-squared forecast errors into firm-specific, industry, and aggregate components. Two possible reasons for the differences in results are: (1) Elton, Gruber and Gultekin (1984) use only three years of data, and (2) they measure the aggregate component by pooling all sample years, instead of measuring year-specific aggregates.

In this paper I attempt to identify the common shocks, by examining macroeconomic news that arrives over an eleven-month forecasting horizon, and relating it to forecast errors. As a first step, I examine the relations between corporate earnings and shocks in industrial production, inflation, interest rates and stock returns. Corporate earnings are sensitive to industrial production and inflation shocks, and this sensitivity does not appear to vary by industry. On the other hand, earnings' sensitivity to changes in interest rates and to unexpected stock returns is highly variable across industries.

After establishing that these macroeconomic shocks are related to corporate earnings, I then examine their relation to analyst forecast errors. I find that the forecast errors likewise reflect shocks in industrial production, interest rates and (in one industry) stock returns, but they do not appear sensitive to inflationary shocks. This brief list of macroeconomic variables explains roughly the same amount of the co-movement in forecast errors as a benchmark index model.

Finally, I investigate whether macroeconomic information in analyst forecast errors may contribute to the observation that analysts tend to overestimate earnings. Previous research documenting this tendency includes Abarbanell (1991), Brown, Foster and Noreen (1985), Fried and Givoly (1982), and Stickel (1990) using Value Line, IBES Summary, Earnings Forecaster and Zacks Detail data, respectively, for various time periods in the 1970s and 1980s. Analyst overestimates are often attributed to a desire to maintain good relations with managers or to retain investment banking business.[5] O'Brien (1988) finds that mechanical time-series models produce larger overestimates of annual earnings than IBES analysts between 1975 and 1981. Since the mechanical models cannot behave strategically, this suggests that the apparent optimism in forecasts during this period may be attributable to unanticipated events. I test this conjecture by adjusting the analyst forecast errors for the macroeconomic news arriving after

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[5]See, for example, Dugar and Nathan (1992), Francis and Philbrick (1993) and Lin and McNichols (1993).

their forecasts were made, and find that analyst forecasts still are significantly optimistic after this adjustment.

In section 2, I describe the portfolio formation methodology and the earnings and forecast data. Section 3 contains a description of the macroeconomic shocks proposed to explain aggregate forecast errors. Sections 4 and 5 contain the results of modeling earnings and forecast errors, respectively, as functions of macroeconomic news. In section 6, I consider whether macroeconomic news can help explain the persistent phenomenon of analyst bias, and in section 7, I summarize the results.

2. Methodology

To reduce the noise in individual observations, I use a portfolio methodology derived from Fama and MacBeth (1973), and group observations into portfolios of firms that are expected to behave similarly. I form portfolios on two dimensions: (1) within industries, based on the assumption that firms in the same industry share operating characteristics that could affect earnings' sensitivity to macroeconomic shocks, and (2) by by fiscal year end, so that the firms in a given portfolio are aligned in calendar time, coinciding with a series of macroeconomic shocks. I describe the industry classification scheme in section 2.1, the earnings and forecast variables in section 2.2, and the portfolio formation methodology in section 2.3.

2.1 Industry Classification

Earnings' relation with macroeconomic events may reasonably be expected to vary across segments of the economy because of variation in firms' real operating characteristics. I divide firms into industry groups using Standard Industrial Classification (SIC) codes as follows.[6]

[6]The SIC codes are from the annual Compustat files. My industry groups are similar, but not identical, to the Industry groupings of the U.S. Office of Managment and Budget. I base my industry groups on exploratory tests of differences in analyst forecast accuracy between industries. I found that Wholesale Trade and Retail Trade are indistinguishable on this dimension, as are Durable and Non-durable Manufacturing. Transportation, on the other

SIC Codes	Industry Group	Abbreviation
10-14	Mining (includes petroleum)	MINING
15-19	Construction	CONSTR
20-39	Manufacturing	MFG
40-47	Transportation	TRANSP
48-49	Utilities & Communications	UTIL
50-59	Wholesale & Retail Trade	TRADE
60-64	Financial (includes insurance)	FINCL
65-69	Real Estate	RL EST
70-89	Services	SERVCS

To make the estimation feasible, I assume that the relation of each macroeconomic factor with earnings is constant through time within an industry, but I allow earnings' and forecast errors' sensitivities to economy-wide factors to vary across industries.

2.2 Earnings and Forecast Errors

In this study, earnings are primary earnings per share (EPS), adjusted for non-recurring items,[7] and scaled by the beginning-of-year stock price. In a perpetuity model of firm value, the earnings/price (EP) ratio represents the capitalization rate of earnings, which in principle depends -- at the firm level -- upon the firm's equity risk and the "quality" or persistence of its earnings. I chose the rate of return form for the earnings variable for the sake of interpreting a linear statistical model. When the unanticipated macroeconomic shocks, which are defined in section 3, are measured in percent-change form and used as regressors, they can be interpreted as additive components of the rate of return in a linear model.[8]

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hand, proved to be distinct from Utilities, and Real Estate is distinct from Financial. I excluded two Agricultural (SIC 01-09) firms from the sample because this industry group is too small to be modeled properly.

[7]Specifically, I subtract the per-share amount of Special Items, Compustat data item 17, from EPS. The earnings forecast data, described later in the text, are from IBES, where officials Dale Berman and Karen Waldemar have stated in private conversations that analysts estimate earnings "from continuing operations." The adjustment for Special Items is also consistent with results of Philbrick and Ricks [1990]. I found that this adjustment resulted in smaller average forecast errors and fewer extreme values than no adjustment, and that not correcting for taxes dominated tax-corrected Special Items.

[8]The macroeconomic variables in this paper are measured in logarithmic, or continuously compounded return form. The statistical fit and regression diagnostics suggest that this model is reasonable.

The analyst forecasts are median earnings forecasts of annual earnings published in the IBES Summary eleven months prior to the fiscal year end. I chose eleven months, the longest span examined in Table 1, to maximize the chance that consistent macroeconomic influences could be found.[9] Forecast errors (FE) are differences between actual earnings and IBES median forecasts, scaled by price. A positive forecast error means that the earnings report was "good news," and that the forecast was pessimistic relative to the reported number. I use fully-diluted earnings to compute the forecast errors whenever IBES indicates that analysts forecast fully-diluted, not primary EPS.

Annual earnings and beginning-of-year prices are from the Compustat Annual data files (including research files), and earnings forecasts are from the IBES Summary database. I omit firm-years in which firms changed fiscal year ends because of the difficulty in determining whether analysts predicted all or part of a fiscal year. The resulting data set has 12,734 firm-year observations on 1,752 different firms.

Table 2 displays the frequency distribution of sample observations along several dimensions. The number of observations per year increases through time, reflecting growth in the IBES database. Since I use Compustat's fiscal year convention, the count for each year includes firms with fiscal years ending between June of that calendar year and May of the following year. I use a version of the IBES Summary tape spanning January 1976 - June 1988, so 1976 includes only December through May fiscal year ends and 1988 includes only June fiscal year firms. Approximately 69% of observations are for December fiscal year firms. The number of observations varies across industries, from 103 firm-years in Construction to 6362 in Manufacturing. This last fact is important for constructing industry portfolios, described below.

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[9]Since the IBES Summary database begins in January 1976, using an eleven-month horizon rather than twelve allows me to include December 1976 fiscal year ends in the sample. Because the database covers 13 years at best, I chose to keep the additional year.

2.3 Portfolio Formation

I compute the average earnings/price ratio and price-scaled forecast error for each industry, from firms whose fiscal years end in each month from December 1976 to June 1988:

$$EP_{IT} = \frac{1}{N_{IT}} \sum_{i=1}^{N_{IT}} EP_{iT} \ , \qquad (1)$$

$$FE_{IT} = \frac{1}{N_{IT}} \sum_{i=1}^{N_{IT}} FE_{iT} \ , \qquad (2)$$

where index i ranges over the N_{IT} firms in industry I whose fiscal years end in month T. The result is 767 industry portfolios distributed over 139 fiscal year end months.

These portfolios are unequal in size because of the uneven distribution of observations across fiscal year ends and industries. More than 25% of industry-month "portfolios" contain only one firm, but the December portfolios of Manufacturing firms contain over 400 observations in the later sample years. The distribution varies widely across industries, as illustrated in the lower portion of Table 2. Since the precision of a mean is proportional to the number of observations used to compute the mean, this unevenness induces heteroskedasticity in EP_{IT} and FE_{IT}. To correct for this heteroskedasticity, I weight each portfolio observation by the number of firms used to compute the average in all the parametric statistical tests.[10]

Table 3 contains descriptive statistics on the sample distributions of earnings and forecast errors before and after portfolio formation. On average, reported earnings are 8 or 9% of price, and the median EP is 9 or 10%. The average forecast error is an overestimate of about 3% of price, and the median is an overestimate of 0-2%. Table 3 shows that portfolio formation reduces the effects of extreme earnings realizations (as expected), since the standard deviations

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[10]Each portfolio observation is divided by $1/_{IT}$. I presume that differences across industries or through time in the underlying variances of earnings or forecast errors are of second-order importance compared to the 400-fold difference between the smallest and largest portfolios.

of EP and FE portfolios are smaller than those of the underlying observations, and extreme observations in both tails are reduced.

3. Macroeconomic Variables

The macroeconomic factors in this study are similar to those proposed by Chen, Roll and Ross (1986), who investigate whether economic forces other than systematic risk explain stock returns. Since my goal is to explain how these economic forces affect earnings and earnings forecast errors, not stock returns, my variable definitions differ somewhat from theirs. The basic series, as in Chen, Roll and Ross (1986) are industrial production, corporate and government bond yields, inflation, and aggregate stock market returns. Since the primary research question concerns information that affects current earnings, but was not available to analysts when they made their forecasts, I measure macroeconomic news that arrives after the forecast publication date and before the fiscal year end. I chose the forecast publication date as the starting point because, though analyst forecasts in monthly published lists are not all concurrent, all were surely produced prior to the publication date, so information released after that date will be news.[11] Outdated forecasts will add noise and tend to reduce the power of statistical tests to reject the null hypotheses in the analyst forecast error regression, but should not introduce bias. I exclude macroeconomic news after the end of the fiscal year because accounting earnings are historical, not prospective.

3.1 Industrial Production

If production translates immediately into profitable sales, industrial production (IP) will be positively associated with contemporaneous earnings. In contrast, production smoothing

[11]This is conditional, of course, on the suitability of my expectations models, which are described in sections 31-3.4. A separate question, which I do not address in this paper, is whether forecasters are efficient users of available macroeconomic data. This question has been examined by Keane and Runkle (1990), Klein (1990), and Abarbanell (1991). The IBES Summary data which I use here are not well suited to studies of efficiency, because the monthly lists may contain outdated forecasts [see O'Brien (1988)], which would bias the investigation toward rejection of efficiency.

models suggest that there should be no relation or a negative relation between production and current profit.[12] I use the Total Index of Industrial Production (1987=100) from the NBER/Citibase economic data base, and define growth in this index in continuously compounded return form:

$$GIP_T = \ln\left(\frac{IP_T}{IP_{T=11}}\right). \qquad (3)$$

GIP_T is the 11-month growth in industrial production ending in month T. Viewing growth in IP as a macroeconomic shock assumes that IP is expected to be level. This is consistent with the perspective taken by Chen, Roll and Ross (1986) and Fama (1990).

In the empirical results reported in section 4, I find a negative relation between GIP and current earnings, which could be consistent with the prediction of production smoothing models. I do not consider leads or lags of IP because, as discussed above, my concern is with information that affects current-year earnings and is released after analysts have made their forecasts.

3.2 Inflation

The impact of unanticipated inflation on a firm's current earnings depends upon the relative rates of inflation for inputs and outputs, the firm's inventory cost-flow assumption (e.g., LIFO or FIFO) and its purchasing behavior. The use of historical cost accounting in the U.S. virtually assures that output price effects will dominate in aggregate, so a positive relation is expected between earnings and unanticipated inflation.

I compute unanticipated inflation from monthly inflation and yields on one-month Treasury bills (T-bills). Both variables are from Ibbotson & Associates' Stocks, Bonds, Bills and Inflation Yearbook (SBBI). If investors believe that the real riskless rate is constant in the short term, then changes in the T-bill rate provide market-based forecasts of next month's inflation.

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[12]Cf. Blinder [1986], Blanchard [1983]. Most production smoothing models are concerned with changes in inventory quantities, which are increased by production and decreased by sales. Empirical evidence for production smoothing in the macroeconomic literature, however, is mixed.

My model for one-month expected inflation is today's inflation plus the change in the one-month T-bill:[13]

$$E_T[I_{T+1}] = I_T + (TB_T - TB_{T-1}) \quad (4)$$

In (4), IT is inflation, TB_T is the T-bill rate and $E_T[.]$ is the expectation operator, all in month T. I project inflation over the 11-month earnings forecasting horizon by compounding the one-month expectation.[14] Unexpected inflation (UEI) is the difference between actual and projected inflation:

$$UEI_T = \left(\sum_{t=T-10}^{T} \ln(1+I_t) \right) - \left(11 \cdot \ln(1+E_{t-11}[I_{t-10}]) \right) \quad (5)$$

The results reported in section 4 indicate that corporate earnings have the expected positive relation with unexpected inflation.

3.3 Interest Rates

The change in interest rates gives a market-based and forward-looking estimate of the interest rates faced by corporations, reflecting prevailing interest rates on long-term risky assets and assessments of corporate debt securities' risk. My proxy for interest rate changes is the change in the Average Yield on Corporate Bonds from NBER/Citibase[15] in log form, or:

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[13]This model differs from the Fama-Gibbons [1984] model used by Chen, Roll and Ross [1986], which adds a (negative) moving average error term for changes in the real rate. The model in equation (2) results in a lower mean-squared-error than the Fama-Gibbons model in predicting 6-month inflation for non-overlapping 6-month periods from July 1970 to December 1988.

[14]This assumes that expected inflation is constant over the eleven-month horizon. Eleven-month bill maturities might be more desirable data to form my estimates, although the assumption that real rates are constant might become strained over that longer interval. I was unable to find a data source with eleven-month maturities of Treasury securities covering this time period.

[15]The bond yield reported in NBER/Citibase is the monthly average of daily observations on the per-annum yield on Moody's Corporate Bond Index. The bonds included in the monthly average have maturities of 15-20 years.

$$IRCH_T = \ln\left(\frac{1+BY_T}{1+BY_{T-1}}\right) \tag{6}$$

where IRCHT is the 11-month change in bond yields (BY) ending in month T. This number can be interpreted as the change in investors' expected or required future returns. In contrast, earnings reflect current realizations of corporate profitability. Consumption smoothing models (e.g., Shiller (1982)) suggest a negative relation between expected returns and current output, as consumers borrow through recessionary periods and save during expansions to smooth their consumption through time. The implication is that interest rates and earnings should covary negatively, though the results reported in section 4, indicate a positive correlation between interest rate changes and earnings that varies across industries.

3.4 Stock Market Returns

Earnings and stock market returns are tautologically related over long enough time periods. While the unexpected market return variable is a broad index of current news that affects corporations, stock returns reflect investor expectations about events beyond the current year, and reported earnings reflect current realizations that may have been partially anticipated in starting prices. These facts lead to a less than perfect, but positive, correlation expected between annual earnings and stock returns for any given firm, and in aggregate.[16]

[16]See Lipe [1990] for a thorough discussion of this relation.

Unexpected stock returns for individual companies are often computed using an estimated version of the Capital Asset Pricing Model (CAPM), relating the firm's return to that of a market portfolio. The same procedure is infeasible for computing the unexpected return on the entire market. Instead, I use corporate bond yields as a proxy for investors' expected return on a long-term risky investment, and compute unanticipated market returns as the difference between realized market returns compounded over the 11-month forecasting horizon and expected returns:

$$UEMR_T = \left[\sum_{t=T-10}^{T} \ln(1+R_{mt}) \right] - \left[\ln\left(1+\frac{11}{12}\cdot BY_{T-11}\right) \right] \qquad (7)$$

In (7), $UEMR_T$ represents the 11-month unexpected market return ending in month T, R_{mt} is the return on the stock market in month t, and BY_{T-11} is the average annual corporate bond yield at the beginning of the forecast horizon.

I use the total monthly return on the S&P 500 from the SBBI in lieu of the market return, and the Average Yield on Corporate Bonds from NBER/Citibase as a proxy for investors' expected returns on risky assets. Of course, the CAPM implies that expected returns for stocks should be higher than those for (relatively-safer) bonds, so BY should systematically underestimate investors' expected equity returns.[17] If investors' perceptions of the <u>relative</u> riskiness of stocks versus bonds is stable over time, this proxy will differ from the true unexpected market return by a constant, with no effect on time-variation, or co-variation with earnings or forecast errors. In the discussion of results, I consider what effect this proxy may have on the estimated constant terms of the regressions. In general, the results reported in section 4 indicate that the relation of earnings with unexpected stock returns is positive, as expected, and the strength of this relation varies across industries.

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[17]Chen, Roll and Ross [1986] use junk bond yields, rather than average bond yields, since junk bonds are presumably closer to equity. However, junk bond issuers are a select group whose high-yield debt is not necessarily less risky than the equity of S&P 500 firms. I have replicated the tests in this paper using junk bond yields instead of average corporate yields, and find very similar results.

3.5 Sample Distributions of Macroeconomic Shocks

I measure macroeconomic shocks over the 11 months prior to the fiscal year end, which is the analyst forecast horizon. The sample includes 139 fiscal year ends from December 1976 - June 1988, so the macroeconomic variables are measured over 139 overlapping 11-month intervals. Table 3 shows that unexpected inflation and interest rate changes are close to zero on average in this period, and their distributions are quite symmetric. Industrial production growth averages about 3% over the period, with a fairly symmetric distribution around this average. Unexpected stock returns average about 2%, consistent with the story that the bond yield proxy systematically underestimates expected returns on stocks.

Spearman (rank-order) and Pearson (product moment) pairwise correlations of the variables are displayed in Table 4. The correlations of EP and FE with other variables are based on 767 industry-month portfolio observations, while the correlations between pairs of macroeconomic variables are based on 139 time-period observations. The EP and FE portfolio observations are weighted by the number of firms in the portfolio for the Pearson correlations, while the Spearman correlations are computed from unweighted observations. The weighted parametric and unweighted non-parametric correlations are qualitatively similar, indicating that the weighting scheme does not dramatically alter the empirical relations. EP has a strong pairwise association with FE, as well as with interest rate changes and unexpected inflation. FE is closely associated with those two macro variables, and with industrial production. These pairwise correlations do not account for differences in associations across industries, which prove to be important aspects of some relations.

4. Earnings' Relation with Macroeconomic Shocks

The investigation of earnings' relation with macroeconomic news is prerequisite to understanding macroeconomic influences on analyst forecast errors. If the macroeconomic shocks as I measure them proved to be unrelated to earnings, then it would not be logical to expect analyst forecast errors to reflect these shocks. Stylized facts about the relation between earnings and macroeconomic news are also interesting in their own right, as they shed light on the sources of common information in corporate earnings.

Table 5 shows two benchmark estimates of average portfolio earnings/price ratios by industry. The first benchmark allows for variation in EP ratios across industries, which is equivalent to a within-sample industry index model. The second benchmark allows for time variation as well. The time variation is expressed as "unobserved heterogeneity" in this model.[18] In other words, the model verifies that EP ratios vary across years, but does not specify what time-specific characteristics contribute to the variation.[19]

Cross-industry variation in EP alone accounts for 70% of the variation in realized EP ratios. Industry averages range from approximately zero for Mining, which includes petroleum extraction firms, to over 12% for the Financial and Utilities groups. The earnings/price ratio for profitable firms should increase with leverage, so the high rates of return for Financial and Utilities firms and the low rate for Services may reflect relative degrees of leverage. It is evident from Mining's negatively-signed return that these are realized, not expected returns. When year dummy variables are introduced, the explanatory power of the two factors together increases to 83%. The estimates of industry average EP conditional on year effects, reported in the right-hand columns of Table 5, are not dramatically different from their unconditional counterparts in the left-hand columns. The significant F statistic on years confirms that there is significant year-to-year variation in earnings/price ratios.

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[18]Cf. Heckman and Singer (1982), Chamberlain (1985).

[19]I use Compustat's fiscal year convention to define years. The implication of this is that the fiscal years of non-December firms are not aligned perfectly with the year indicators. This will reduce the ability of the benchmark model to distinguish year effects in the data.

The maintained hypothesis of this study is that macroeconomic news is an observable, time-specific characteristic that affects earnings and forecasts. The goal of the EP model, therefore, is to find macroeconomic variables that describe the time-variation in earnings/price realizations. The results in Table 6 are for the following regression of earnings in return form on growth in industrial production, unexpected inflation, interest rate changes and unexpected stock returns:

$$EP_{IT} = \alpha_I + \beta_1 GIP_T + \beta_2 UEI_T + \beta_{3I} IRCH_T + \beta_{4I} UEMR_T + e_{IT} \quad (8)$$

The macroeconomic shocks are expressed as logarithmic returns, which allows the shocks to be interpreted as additive components of the rate of return in a linear model. I allow the relation of earnings with the macro shocks to vary across industries, but assume it is constant through time for estimation. Cross-industry variation in the relations of EP with GIP and UEI proved to be statistically insignificant at conventional levels, so β_1 and β_2 are estimated as constants across industries in Table 6.

When observed macroeconomic characteristics replace the year dummy variables as expressions of time-varying characteristics, explanatory power is about 75%, as compared with 70% for industries alone and 83% for industries with year effects.

Two reasons that the non-specific year-effect model is likely to explain more of the variation in EP ratios than the model using specific, observed time-specific variables are (1) the list of macroeconomic variables is undoubtedly incomplete, and (2) the macroeconomic variables are measured as shocks, not levels.[20] Earnings may be affected by both expected and unexpected inflation, for example, but variation in expected inflation across years is not included in equation (8). Recall that the primary motivation for the earnings model is as a precursor to the

[20]A third reason, related to item (2), is that the macroeconomic variables are measured over only 11 months, while earnings cover 12 months.

forecast error investigation, to demonstrate that the shocks I have measured are relevant to earnings, so that it is reasonable to think they may be impounded in forecast errors.[21]

Since the annual earnings periods of successive fiscal year end months overlap (e.g., the fiscal year ending December 1985 overlaps for 11 months with the fiscal year ending January 1986), there is a potential for serial correlation in the residuals. This potential is mitigated by the two facts: (1) firms in consecutive portfolios are different firms (e.g., December year end firms, followed by January year end firms) and (2) the model purges the residuals of whatever common information is impounded in the macroeconomic shocks. The Manufacturing industry group was the only group with an uninterrupted time-series of 139 observations, so I used this group to test for first order serial correlation in the residuals. I found no measurable serial correlation.[22]

Estimates of the average EP by industry, conditional on the macroeconomic shocks are similar to those reported in Table 5. The relations of earnings with GIP and UEI are consistent with predictions. A 1% acceleration in industrial production is associated with a drop of about .3% in earnings, consistent with production-smoothing model predictions. A change in unexpected inflation of 1% is associated with an increase in earnings of about .2%, reflecting the fact that inflation shocks affect revenues more directly than expenses for firms using historical cost accounting. Earnings are positively related to interest rate changes for most industries, and this relation is strongest in Construction, Mining and Transportation, where a 100 basis point increase in corporate bond yields is associated with a 2-3% increase in earnings. Unexpected stock returns are significantly positively associated with earnings in the Financial, Mining, and Manufacturing industries, but the relation is indistinguishable from zero in several industries.

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[21]This failure to include the expected counterpart of each of the macroeconomic shocks in the earnings regression may create an omitted variables problem. When an omitted variable is correlated with regressors in the model, the estimated coefficients on included variables will be biased. This problem is mitigated somewhat by the fact that these regressors are shocks, and so should be orthogonal to their respective expected components.

[22]For the EP regression, first-order serial correlation of the Manufacturing residuals is 0.08 and the Durbin-Watson statistic is 1.72. For the FE regression, first-order correlation is -0.00 and the Durbin-Watson statistic is 1.96. In both regressions, correcting for residual correlation up to lag 12 had negligible effects on the results.

The fact that some of the coefficients vary across industries confirms the importance, noted by Magee (1974), of industry factors in aggregate earnings movements. This variation is not consistent with results reported by Gonedes (1973), who fails to find industry influences. Magee (1974) suggests that differences in their results may be due to differences in industry classification, but the classifications in Magee (1974) are finer than those in Gonedes (1973), while mine are coarser.

In summary, macroeconomic shocks to industrial production, inflation, interest rates and stock returns have significant descriptive power over industry earnings/price ratios, though not as much as an "unobserved heterogeneity" model. The sensitivities of earnings to interest rate shocks and to unexpected stock returns are industry-specific, while earnings sensitivities to industrial production growth and to inflation shocks appear constant, economy-wide.

5. Forecast Errors' Relation with Macroeconomic Shocks

The results in Table 6 confirm that macroeconomic shocks are related to current earnings. I next investigate whether this news shows up in analyst forecast errors, using a regression equation analogous to (8) with forecast errors replacing earnings as the dependent variable:

$$FE_{IT} = \gamma_I + \delta_1 GIP_T + \delta_2 UEI_T + \delta_{3I} IRCH_T + \delta_{4I} UEMR_T + \varepsilon_{IT} \qquad (9)$$

The information in Tables 7 and 8 is analogous to that in Tables 5 and 6, respectively, but with forecast errors as the dependent variable. Table 7 shows that average forecast error is significantly negative at the 3% level or better in all 9 industries, whether or not the averages are conditioned on year. Table 7 confirms the result available in Table 1, that average forecast errors over an eleven-month horizon vary significantly from year to year.

Comparing the regression model of Table 8 with the two-factor model in Table 7 shows that the macroeconomic shocks explain nearly as much of the variation in forecast errors as the "unobserved heterogeneity" or year-effect model, both about 47%. This performance relative to the benchmark model is much better than we observed in the earnings regression (8). A likely reason for the improved relative performance is that in equation (9), both the dependent variable and the regressors are measured as innovations.

The industry intercepts from the regression model in Table 8 are all similar to their counterparts in Table 7 in magnitude and statistical significance, and indicate that average forecast errors are optimistic by 2-8% of price. Average forecast errors are smallest (in absolute value) in Utilities and in Wholesale and Retail Trade, perhaps reflecting relatively low earnings volatility in these industries.

A 1% increase in industrial production is associated with an average .1% increase in forecast error, in contrast to the negative relation of GIP with EP. Unexpected inflation appears unrelated to forecast errors. Interest rate changes have the strongest association with forecast errors for Construction, Mining and Transportation firms, which were also the industries with the greatest sensitivity of earnings to interest rates. Unexpected stock returns are reliably related to forecast errors only for Financial firms. Thus, there are some parallels between the earnings model and the forecast error model, but they do not match perfectly. A possible reason for differences is that analysts could be better at forecasting the macroeconomy than my expectations models are. For example, if analyst inflation predictions are better than those generated by equation (4), and analysts include their inflation predictions in their earnings forecasts, then their forecast errors need not be related to my measure of "unexpected" inflation.

In summary, macroeconomic shocks to industrial production, interest rates and stock returns have as much descriptive power over industry average forecast errors as an "unobserved heterogeneity" model. Unexpected inflation has no descriptive power. As was true in the earnings/price regression, the sensitivities of forecast errors to interest rate shocks and to unexpected stock returns are industry-specific. Forecast error sensitivity to industrial production growth appears constant economy-wide and positive, which is opposite in sign to the relation between earnings/price and industrial production.

6. Macroeconomic Shocks and Analyst Optimism

O'Brien (1988) found that analysts were less optimistic than mechanical time-series models during the period 1976-1981. Since univariate models clearly have no strategic motives, this result suggests that the perceived "optimism" may have been a time-period-specific phenomenon. Since the macroeconomic shocks do a reasonably good job of explaining time-specific variation in forecast errors, it is possible that they could explain some of the persistent phenomenon of analyst optimism. This question can be addressed by examining the estimated industry constants in Table 8 and comparing them with those in Table 7. The industry constants estimate the industry average rate of return if the macroeconomic shocks had been held at zero, and are measured from time-series observations.

Purging the forecast errors of the effects of macroeconomic news that arrived over the forecast horizon does not eliminate analysts' consistent overestimation. All industry groups have negative average forecast errors in Table 8. In many cases, the average forecast errors are larger, not smaller, after adjusting for macroeconomic influences. There is no evidence that these macroeconomic shocks are the source of analyst optimism, which lends additional credibility to stories that analysts bias their forecasts to maintain good relations with corporate management.

Of course, to the extent that my selection of macroeconomic variables is incomplete or incorrectly measured, analysts' optimistic bias might be explained by events I have failed to include or have mismeasured. An example of such a possible misspecification is bond yields' systematically underestimating expected equity returns. Unexpected market returns as I have measured them average about +2% in this time-period, consistent with an omitted risk differential between debt and equity. While a constant differential does not affect the regression slope coefficient estimates, it does affect the estimated intercept, on which the conclusions about bias from Table 8 are based. However, to eliminate the average analyst forecast error of -3.53% in the Financial Industry (the only industry in which the slope coefficient on the unexpected market return proved significant in Table 8) the "true" unexpected market return in this time period would have to be lower by -3.53/.23, or -15.3 per 11-month interval. Since realized returns in this time period averaged 15.5% per year, this implies that investors expected returns on equity securities to be more than 30% per year over this 12-year period, which seems implausibly large. Therefore, the result that analysts overestimate seems robust to this possible misspecification.

Butler and Lang (1991) show that an individual analysts' optimism or pessimism relative to other analysts tends to persist through time. This study suggests that, in addition, optimism is the predominant sentiment among analysts, since the median analyst forecast consistently overestimates earnings even after controlling for macroeconomic news.

7. Conclusion

The main results of the paper are: (1) macroeconomic news about industrial production, inflation, interest rates and market returns arriving during the year explains some of the time variation in corporate earnings, (2) macroeconomic news that arrives after analysts have made current-year earnings forecasts is reflected in their forecast errors, and (3) in spite of this, controlling for the effects of macroeconomic news does not alter the fact that analysts significantly overestimate earnings on average. This is consistent with conventional wisdom that analysts are optimists.

The strong relation between macroeconomic news and forecast errors confirms that there is an aggregate component to forecast errors corresponding to information analysts did not have at the time they produced their forecasts. An implication of this is that forecast errors for different firms made over the same horizon are not independent observations, but are positively correlated by their common aggregate component.

The macroeconomic variables were measured in innovation form, to match the time span of the forecast errors. Nevertheless, these variables showed strong explanatory power for aggregate earnings/price ratios. Exploring how the levels, not shocks, of these macroeconomic variables are related with corporate earnings could be a fruitful area for future investigation, to provide additional information about the causes of earnings co-movements.

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Table 1

The Significance of Time-period-specific Information in Analyst Forecast Errors, by Forecast Horizon and Fiscal Yearend[23]

Fiscal Year End		Forecast Horizon, in Number of Months Prior to Fiscal Year End: 1	6	11
March	F statistic[24]	0.74	0.93	1.30
	p-value	(0.704)	(0.510)	(0.224)
	R-squared[25]	2.64%	3.30%	4.42%
	N	310	312	321
June	F statistic	1.34	2.65	4.04
	p-value	(0.199)	(0.003)	(<0.001)
	R-squared	1.87%	3.62%	5.32%
	N	782	788	802
September	F statistic	2.08	2.35	2.66
	p-value	(0.025)	(0.010)	(0.003)
	R-squared	3.20%	3.58%	3.97%
	N	638	644	654
December	F statistic	5.60	10.97	18.73
	p-value	(<0.001)	(<0.001)	(<0.001)
	R-squared	0.71%	1.37%	2.29%
	N	8624	8709	8797

[23]The sample for this table consists of non-agricultural firms with Compustat earnings, price and share data and IBES analyst forecasts, with fiscal years ending in March, June, September or December. The data sources and sample selection are described more fully in section 2.

[24]The F statistic tests the hypothesis that average forecast error is the same in all years, and the rejection probability is indicated by the p-value in parentheses below it. There are 12 years, 1976-1988, in the dataset.

[25]The R-squared is from the regression of forecast errors on year dummy variables.

Table 2

Frequency Distributions of Sample Observations by Year, Fiscal Year End and Industry Group

Fiscal Year	Frequency	Percent
76	434	3.4
77	553	4.3
78	639	5.0
79	950	7.5
80	1016	8.0
81	1066	8.4
82	1121	8.8
83	1197	9.4
84	1301	10.2
85	1405	11.0
86	1438	11.3
87	1520	11.9
88	84	0.7
Total	12724	100.0

Fiscal Yearend	Frequency	Percent
1	472	3.7
2	206	1.6
3	320	2.5
4	234	1.8
5	243	1.9
6	802	6.3
7	214	1.7
8	224	1.8
9	654	5.1
10	307	2.4
11	264	2.1
12	8784	69.0
Total	12724	100.0

Industry Group	Frequency	Percent	Number of Portfolios[26]	Average Number of Observations Per Portfolio
CONSTR	103	0.8	50	2.1
FINCL	1541	12.1	53	29.2
MFG	6361	50.0	139	45.8
MINING	524	4.1	64	8.2
RL EST	313	2.5	98	3.2
SERVCS	697	5.5	129	5.4
TRADE	1098	8.6	129	8.5
TRANSP	329	2.6	44	7.5
UTIL	1758	13.8	61	28.8
Total	12724	100.0	767	

[26]Portfolios are formed within industry groups, each month from December 1976 to June 1988, from firms whose fiscal years end that month.

Table 3

Characteristics of the Sample Distributions of Earnings, Forecast Errors and Macroeconomic Variables, 1976-1988[27]

Variable	N	Mean	Standard Deviation	Skewness	Median	Minimum	Maximum
Individual Firm-Year Observations:							
EP	12724	9.11	18.28	-7.56	10.15	-421.18	291.32
FE	12724	-3.11	15.52	-4.17	-0.63	-345.88	331.34
Industry-Fiscal Yearend Portfolios:[28]							
EP	767	7.98	11.56	-4.99	8.61	-124.77	51.13
FE	767	-3.29	10.08	-6.54	-1.63	-129.38	26.77
Macroeconomic Variables:							
GIP	139	2.82	4.21	-0.11	2.93	-5.83	12.01
IRCH	139	0.09	1.47	-0.16	0.33	-3.04	3.51
UEI	139	-0.05	3.38	-0.15	-0.14	-10.26	9.58
UEMR	139	1.88	13.44	-0.00	3.52	-25.53	36.36

[27] All variables are in percent form. EP is the earnings/price ratio; FE is the median analyst forecast error scaled by price; GIP is the growth in industrial production; IRCH is the change in the average corporate bond yield; UEI is unexpected inflation; and UEMR is the unexpected market return. The macroeconomic variables (GIP, IRCH, UEI, UEMR) are computed as logarithmic returns.

[28] Portfolios are formed by industry group, each month from December 1976 to June 1988, comprising firms whose fiscal years end that month. The distribution characteristics for the portfolios of EP and FE are computed from the unweighted observations.

Table 4

Pearson and Spearman Correlations and Associated p-values for Earnings and Forecast Error Portfolios and Macroeconomic Variables, 1976-1988[29]

Pearson Correlations are above the primary diagonal.
Spearman Correlations are below the primary diagonal[30]

	EP	FE	GIP	IRCH	UEI	UEMR
EP	1.000	0.795	-0.062	0.226	0.082	0.067
	.00	.00	.09	.00	.02	.06
FE	0.688	1.000	0.164	0.254	0.087	-0.038
	.00	.00	.00	.00	.02	.29
GIP	-0.043	0.130	1.000	0.129	0.339	-0.134
	.24	.00	.00	.13	.00	.12
IRCH	0.222	0.224	0.093	1.000	0.134	-0.402
	.00	.00	.28	.00	.12	.00
UEI	0.090	0.097	0.371	0.081	1.000	0.020
	.01	.01	.00	.34	.00	.81
UEMR	-0.058	-0.091	-0.218	-0.364	0.053	1.000
	.11	.01	.01	.00	.54	.00

[29] EP is the earnings/price ratio; FE is the median analyst forecast error scaled by price; GIP is growth in industrial production; IRCH is the change in the average corporate bond yield; UEI is unexpected inflation; and UEMR is the unexpected market return. The macroeconomic variables (GIP, IRCH, UEI, UEMR) are computed as logarithmic returns. The correlations of EP and FE with other variables are based on N=767 industry portfolios formed at fiscal yearends from December 1976 to June 1988. Correlations between pairs of macroeconomic variables are based on N=139 time periods.

[30] The Pearson correlations of EP and FE with other variables are weighted by the number of observations in the portfolio. All Spearman correlations are unweighted.

Table 5

Average Earnings/Price Ratios by Industry, 1976-1988[31]

Coefficient Estimates and t-Statistics:

Industry Group	Unconditional[32] I	Unconditional[32] t(I)	Conditional on Year[33] I	Conditional on Year[33] t(I)
CONSTR	5.32	2.15	6.19	3.28
FINCL	12.66	19.80	13.79	26.72
MFG	8.66	27.54	9.16	32.32
MINING	-1.69	-1.55	-0.75	-0.88
RL EST	7.95	5.61	10.19	9.31
SERVCS	6.59	6.93	7.95	10.73
TRADE	8.81	11.64	9.79	16.42
TRANSP	7.19	5.20	7.57	7.12
UTIL	12.84	21.45	13.29	27.41

Sample Size, Adjusted R2 and F-statistics (p-values in parentheses):

	Unconditional	Conditional on Year
N	767	767
Adjusted R2	.707	.831
F-statistics:		
Model	206.61	180.37
	(.00)	(.00)
Industry	206.61	38.59
	(.00)	(.00)
Year	---	47.25
		(.00)

[31]The averages are based on 767 industry group-fiscal yearend portfolios, formed within industry at fiscal year ends from December 1976 to June 1988.

[32]Unconditional average EP ratios are computed for industry portfolios through time using a dummy variable regression. Each observation is weighted by the number of firms in the portfolio.

[33]The conditional weighted average EP is computed using a dummy variable regression with industry and year variables, so the estimated industry averages are conditional on years. Each observation is weighted by the number of firms in the portfolio.

Table 6

Relation of Earnings/Price with Macroeconomic Shocks, 1976-1988[34]

Coefficient Estimates and t-Statistics:

Industry Group	Intercept I	t(I)	GIP 1	t(1)	UEI 2	t(2)	IRCH 3I	t(3I)	UEMR 4I	t(4I)
All			-0.29	-4.88	0.22	3.28				
CONSTR	5.89	2.60					3.69	2.16	-0.05	-0.23
FINCL	12.94	21.49					1.54	3.23	0.37	5.27
MFG	9.08	28.12					1.95	9.06	0.07	2.49
MINING	-1.68	-1.65					3.61	4.80	0.39	3.59
RL EST	8.22	6.23					1.69	1.64	0.22	1.94
SERVCS	7.05	7.89					0.91	1.38	0.14	1.80
TRADE	9.37	12.99					1.43	2.66	0.09	1.52
TRANSP	7.45	5.85					2.29	2.39	0.16	1.19
UTIL	13.25	23.31					0.32	0.79	0.04	0.72

Sample Size, Adjusted R2 and Full Model F-statistic:

N	767
Adj. R2	.764
F-stat.	84.14
p-value	.00

Incremental F-statistics (p-values in parentheses):

	Intercept	GIP	UEI	IRCH	UEMR
Variable[35]	N/A	23.86 (.00)	10.76 (.00)	15.04 (.00)	6.35 (.00)
Industry[36]	176.94 (.00)	0.88 (.53)	0.79 (.61)	3.10 (.00)	3.42 (.00)

[34] The earnings/price ratios are averages for 767 industry portfolios formed at fiscal year ends from December 1976 to June 1988. GIP is growth in industrial production, UEI is unexpected inflation, IRCH is the change in the average corporate bond yield, and UEMR is the unexpected market return. The macroeconomic variables are measured over 11-month intervals prior to year end.

[35] The F-statistic on each variable tests the hypothesis that the variable adds explanatory power to the model. For GIP and UEI, this is the square of the t-statistic. For IRCH and UEMR, whose coefficients vary across industries, the null hypothesis is that at least one industry has a non-zero coefficient.

[36] The null hypothesis for the industry F-statistic for each variable is that all industries are alike in the sensitivity of earnings to this variable.

Table 7

Average Forecast Error/Price Ratios by Industry, 1976-1988[37]

Coefficient Estimates and t-Statistics:

Industry Group	Unconditional[38] I	Unconditional[38] t(I)	Conditional on Year[39] I	Conditional on Year[39] t(I)
CONSTR	-6.65	-3.64	-6.04	-3.65
FINCL	-2.91	-6.16	-2.31	-5.09
MFG	-3.21	-13.82	-2.77	-11.12
MINING	-7.75	-9.56	-7.09	-9.49
RL EST	-2.39	-2.28	-1.27	-1.32
SERVCS	-3.53	-5.03	-2.79	-4.29
TRADE	-2.45	-4.37	-1.81	-3.46
TRANSP	-5.21	-5.09	-4.83	-5.17
UTIL	-1.32	-2.99	-0.90	-2.11

Sample Size, Adjusted R2 and F-statistics (p-values in parentheses):

	Unconditional	Conditional on Year
N	767	767
Adjusted R2	.349	.471
F-statistics:		
Model	46.46	33.38
	(.00)	(.00)
Industry	46.46	8.97
	(.00)	(.00)
Year	---	15.55
		(.00)

□

[37]The forecast errors are actual EPS, adjusted for Special Items, minus the median analyst forecast from the IBES Summary 11 months prior to the fiscal year end. The averages are based on 767 industry group-fiscal yearend portfolios, formed within industry at fiscal year ends from December 1976 to June 1988.

[38]Unconditional average forecast errors are computed for industry portfolios through time using a dummy variable regression. Each observation is weighted by the number of firms in the portfolio.

[39]The conditional weighted average forecast error is computed using a dummy variable regression with industry and year variables, so the estimated industry averages are conditional on years. Each observation is weighted by the number of firms in the portfolio.

Table 8

Relation of Forecast Error/Price with Macroeconomic Shocks, 1976-1988[40]

Coefficient Estimates and t-Statistics:

Industry	**Intercept**		**GIP**		**UEI**		**IRCH**		**UEMR**	
Group	**I**	**t(I)**	**1**	**t(1)**	**2**	**t(2)**	**3I**	**t(3I)**	**4I**	**t(4I)**
All			0.12	2.81	0.04	0.84				
CONSTR	-6.96	-4.16					2.74	2.17	-0.08	-0.45
FINCL	-3.53	-7.95					-0.18	-0.52	0.23	4.59
MFG	-3.62	-15.22					1.20	7.56	0.00	0.22
MINING	-8.09	-10.83					3.30	5.95	0.00	0.05
RL EST	-3.00	-3.09					0.84	1.10	0.16	1.83
SERVCS	-4.01	-6.09					0.41	0.85	0.06	1.16
TRADE	-2.80	-5.26					0.33	0.84	0.02	0.45
TRANSP	-5.77	-6.15					1.75	2.47	0.10	0.32
UTIL	-1.70	-4.07					0.15	0.50	-0.01	-0.23

Sample Size, Adjusted R2 and Full Model F-statistic:

N	767
Adj. R2	.467
F-stat.	24.13
p-value	.00

Incremental F-statistics (p-values in parentheses):

	Intercept	**GIP**	**UEI**	**IRCH**	**UEMR**
Variable[41]	N/A	7.90	0.70	11.70	3.03
		(.01)	(.40)	(.00)	(.00)
Industry[42]	43.85	1.87	0.96	10.12	7.12
	(.00)	(.06)	(.47)	(.00)	(.00)

[40]The forecast errors are actual EPS, adjusted for Special Items, minus the median analyst forecast from the IBES Summary 11 months prior to the fiscal year end. The observations used in this table are averages for 767 industry portfolios formed at fiscal year ends from December 1976 to June 1988. GIP is growth in industrial production, UEI is unexpected inflation, IRCH is the change in the average corporate bond yield, and UEMR is the unexpected market return, all measured over the 11-month horizon. Each observation is weighted by the number of firms in the portfolio.

[41]The F-statistic on each variable tests the hypothesis that the variable adds explanatory power to the model. For GIP and UEI, this is the square of the t-statistic. For IRCH and UEMR, whose coefficients vary across industries, the null hypothesis is that at least one industry has a non-zero coefficient.

[42]The null hypothesis for the industry F-statistic for each variable is that all industries are alike in the sensitivity of earnings to this variable.