Preliminary. Comments welcome.

Please do not circulate or cite.

Does Analyst Bias Drive Stock Return Anomalies? An Empirical Investigation

Ravi Jagannathan

Department of Finance

Kellogg Graduate School of Business

Northwestern University, Evanston, IL 60208

rjaganna@nwu.edu, 847-491-8338

and

NBER

Tongshu Ma

Department of Finance

David Eccles School of Business

University of Utah, Salt Lake City, UT84112

fintsm@business.utah.edu, 801-581-7506

António Baldaque da Silva[1]

Department of Economics

Northwestern University

[1]We thank the helpful comments and suggestions of Paul Pengjie Gao. We are responsible for any errors and omissions. We acknowledge the use of I/B/E/S data, a service of Thomson Financial, in our study. This data has been provided as part of a broad academic program to encourage research on analysts' expectations.

Abstract

We study the relation among analyst forecast bias, firm characterstics, and equity return anomalies. We propose simple corrections for the raw analyst forecasts and document that these corrections significantly reduce the forecast error. We aggregate individual stocks into portfolios that are commonly studied in finance and examine analyst forecast bias at portfolio levels. We find that analysts forecasts are too high over all portfolios of interest and are particularly high for small/growth and small/loser stocks. This means on average analysts show the same optimism for these stocks as investors do, as postulated in the behavioral explanation of equity return anomalies. However, we find that we cannot use analyst optimism to construct portfolios that earn significantly abnormal return once other firm characteristics are controlled for.

In this paper we examine analysts earnings forecasts at portfolio level and study the relation among analyst forecast bias, firm characteristics, and equity return anomalies.

There are three motivations for this study. First, analysts earnings forecast is an important source of information for the valuation of equity assets (see e.g., Frankel and Lee (1998)). However, there seems to be a gap between empirical studies of earnings forecasts and, in particular, their biases on the one hand, and asset returns and valuations on the other. The former, concentrated in the accounting literature, are usually done at the individual stock level, while the latter, concentrated in the finance literature, are ususally done at the portfolio level. This gap raises two questions. First, it is difficult to gauge how important the empirical findings about earnings forecast bias are for asset valuation. Second, it is well documented in the literature that analyst forecasts have "biases" and are too optimistic (see e.g., Abarbanell and Lehavy (2003) and the references therein). However, these studies are based on individual stocks. How do these biases carry over to asset classes and to what extent? If a bias takes a simple form it should be possible to correct for it. How do corrected forecasts perform? In contrast to existing studies that focus on analysts forecasts at individual stock level, we examine these questions at portfolio level.

The second motivation is that existing rational expectations models of asset pricing are challenged by various return anomalies. For example, in the intermediate term of several months to a year, losers (those stocks that show lower returns) continue to lose and winners continue to win. One line of explanation for these return anomalies is that investors are not perfectly rational, instead they have various behavioral biases. Investors tend to be too optimistic about certain class of assets. They will value these assets too high and these assets' future return will be too low, relative to that predicted by the rational expectations model. One important question is whether analysts show that same behavioral bias in their forecasts. Are these return anomalies related to systematic bias in earnings forecasts? Given that analysts and investors are exposed to similar information, if we find that analysts show the same behavioral bias as postulated by the behavioral explanations about investors, then this makes the behavioral explanation more plausible.

The third motivation is that, if analysts show the same behavioral bias as investors do, then whether their biases affect asset returns or the biases are already factored in by the investors.

We find that analyst forecast errors vary systematically with firm characteristics. Analysts tend to be more optimistic about stocks, such as growth stocks and stocks with high turnover, that have been documented in the literature to exhibit lower future returns. The behavioral explanation of equity return anomalies postulate that such stocks exhibit lower future returns because of investors' over-optimism about their future earnings. Our findings suggest that the pattern of analysts optimism is the same as that of investor optimism suggested by the behavioral theory. However, our findings seem to suggest that analyst biases are not the driving force of the asset return anomalies. That is, controlling for firm characteristics, analyst biases does not indicate future abnormal returns in one way or the other.

The paper is organized as follows: Next section gives a brief literature review. Section two gives a summary of earnings forecasts. In Section three we describe our sample and the variables used. Section four discusses the adjustments we introduce into the analysts forecasts and describe the alternative forecasts we will compare. Section five presents the empirical results about systematic variations of analyst forecast bias, firm characteristics, and future stock returns. Section six concludes.

1 Literature Review

Dechow and Sloan (1997) examines the ability of naive investor expectations models to explain the profitability of contrarian investment strategies. They find no systematic evidence that stock prices reflect naive extrapolation of past trends in earnings and sales growth. However, consistent with Bauman and Dowen (1988) and La Porta (1996), they find that stock prices naively reflect analysts' biased forecasts of future earnings growth, and this can explain over half of the higher returns to contrarian investment strategies.

Dechow and Sloan examines the naive extrapolation hypothesis of Lakonishok, Shleifer, and Vishny (1994) (LSV henceforth) about the contrarian strategy. Our research complements Dechow and Sloan in two aspects. First, the scope of our research is wider: we examine the systematic variations in analyst bias and how this is related to firm characteristics along various dimensions such as size, book-to-market, etc. On the other hand, we do not intend to formally and quantitatively test any specific hypothesis about equity return anomalies. This is partly due to fact that doing so would require us to use a specific asset pricing model. (Dechow and Sloan uses the dividend growth model of Gordon (1962).) We are reluctant to use an asset pricing model because if we concede that investors are irrational, then asset pricing models such as the dividend growth model or CAPM are likely to be inapplicable.

Frankel and Lee (1998) examines whether using an analyst-based valuation model can predict cross-sectional stock returns. They use the I/B/E/S consensus forecasts and the residual income model to estimate firms' fundamental value (V). They find that the ratio of fundamental value to stock price (V/P) is a good predictor of long-term (one to three years) cross-sectional stock returns. Similarly, Givoly and Lakonishok (1979) finds that analyst forecast revisions contain information about future stock return. However, Guay et al. (2003) estimate the "implied cost of capital" from analysts' short- and long-term earnings forecasts, and find that the implied cost of capital estimates are uncorrelated with future annual and monthly returns. The results of Frankel and Lee and Givoly and Lakonishok seem to suggest that analysts forecast are more rational than investors' expectations. Our results, however, indicate that analysts show the same pattern of systematic bias as investors do, and analyst bias are already factored in the stock prices. The latter result is consistent with Guay et al. (2003).

Kothari et al. (2004) studies the stock market's reaction to aggregate earnings news. They find that the market reaction to earnings news is different at aggregate level than at the individual stock level. Their study is a time series one while our focus is the cross-sectional differences in earnings forecast bias and equity return anomalies. Also, their earnings news is defined as the difference between this quarter's aggregate earnings and that of four quarters ago, while we use analyst forecast bias.

Chan et al. (1999) find that momentum strategies based on both past return and earnings momentums earn higher abnormal return than those based solely on price momentums. This result indicates that the market is slow in incorporate the full impact of earnings information in its valuation. This is consistent with the post-earnings announcement drift literature of Latane and Jones (1979) and Bernard and Thomas (1989), among others. These results indicate that investors are not totally rational. In contrast, our focus is on analysts.

2 Sample and Variables Used

We start with the CRSP and Compustat merged database (CCM). We do not exclude the financial institutions (companies with 4 digit SIC code between 6000 and 7000). Then we merge CCM with the I/B/E/S sample, in order to get the forecasts from analysts surveyed by I/B/E/S International Inc. Each observation constitutes a firm/year pair. The month of the year chosen corresponds to nine months before the end of the fiscal year. We choose this date so that: (i) the earnings from the previous year are already released (at least for the majority of the firms) and (ii) the earnings from the first quarter of the current year are not yet known.

We will use three forecast items from IBES. Forecasts of earnings for current fiscal year is denoted as FY0 (fiscal year zero). Forecast for the next fiscal year is FY1. LRG represents the analyst forecasts of long run growth rate in EPS (earnings per share). LRG is usually interpreted as the growth rate in EPS for the three years following FY1. Here we maintain this interpretation. Unless otherwise noticed, we use the term analyst forecasts to refer to the median forecast for a certain firm/year/forecast horizon released by I/B/E/S. This is the median of all forecasts received by I/B/E/S until the Thursday before the third Friday of the month (always between the 14th and the 20th of each month), adjusted to basic if reported in I/B/E/S on a diluted basis.

In order to aggregate forecasts for individual companies into forecasts for a portfolio, we normalize earnings and earnings forecasts into "per dollar" basis, as below. When referring to a "per dollar" variable in year t, we mean the value of the variable for the stock divided by the price of one current share twelve months before. For example, earnings per dollar for FY1 is the actual earnings per share for year $t + 1$, divided by the share price at time $t - 1$, both for one time t share. One just has to remember that at time t, for all the lead and lag per dollar variables, the "per dollar" means divided by the $t - 1$ price of one current share. We choose to divide by the price twelve months before because our momentum portfolios are based on the previous twelve months return. Unless otherwise noticed, we aggregate firm-level quantities into portfolio level quantities using value-weighted averages, using the market capitalizations at the time of portfolio formation as the weights.

We merge CCM with I/B/E/S using historical cusip number. After merging with I/B/E/S the sample is called CCIM (Crsp/Compustat/I/B/E/S Merged). We require an observation in CCIM to have at least one of the three analyst forecast items mentioned before in a year. To this sample, we applied the cleaning process. The final sample, CCIMC or CCIM Cleaned, is the one we use throughout the paper. It has 47,283 observations, spanning from 1982 (1,661 observations) to 2001 (2,241 observations). The maximum number of observations per year is 3,234 in 1998.

In Panel A of Table 1 we compare the different samples and provide evidence of the importance of the cleaning process referred above. Merging the CCM sample with I/B/E/S loses an important number of observations (firm/year pairs) but only a trivial amount in terms of total market capitalization. After the cleaning process, we end up with around 61% the observations of CCM, representing 96% of the CCM market capitalization. Panel A also shows that before the cleaning the standard deviation of the forecasting error is unworkable (almost twice the average earnings per dollar). It is clear that the process allow us to get rid of lots of uninformative forecasts: the standard deviation of forecast error is reduced by about 30%. With no cleaning, the exercise we propose in this paper is not very useful.

Panel B of Table 1 details the criteria used in the cleaning process. The criteria described use only ex-ante data. Although the criteria are subjective, it seems intuitive in identifying potential problematic forecasts. For instance, if the standard error of the forecasts from different analysts is high, this may signal difficulties in forecasting or divergence of opinion among analysts. One may expect a higher variance of the forecasting errors for these stocks. Note that we were parsimonious in the cleaning process, with few observations being cleaned by each criterion.

For the analysis we do later in this paper, it is important to understand the size, book to market, and momentum characteristics of the sample we use in this work. Specifically, we construct portfolios based on size and book-to-market as described in Fama and French (1992), applied to our CCM sample. This guarantees that a particular observation in our sample is virtually in the same portfolio as it is in FF92. (The returns of 10 size and 10 book-to-market decile portfolios that we constructed have correlations with the corresponding returns reported on Professor French's website well above 99% over the sample period.) The momentum portfolios are formed analogously, with the returns over the previous twelve months substituting the size or book-to-market variable in the procedure. The only difference is that momentum portfolios are formed monthly. (The returns of the empirical return factor, UMD, that we constructed have correlations with the corresponding returns reported on Professor French's website well above 99% over the sample period.)

In panel A of Table 2 we present the number of observations in the initial sample and after its merging with I/B/E/S and cleaning process. As we can see, these two steps erase a disproportional number of small firms, especially those with high book-to-market ratio and bad performance over the previous year. This is hardly surprising: the fraction of small firms not covered by I/B/E/S is clearly higher than that fraction for larger ones, so the merging and cleaning processes suppresses them. Moreover, the commercial relevance of following a firm that has bad past performance (and so is more likely to have a high book-to-market ratio), if the firm still exist, is probably small, so it is not surprising that analysts stop following them.

Another problem we have to debate while constructing our sample is the survival bias. For a large number of observations (increasing with the forecast horizon), the stock for which the forecast is made does not actually exist when the forecast period actually comes. Suppose we consider an earnings forecast for a certain firm but that some time later the firm is delisted. This may happen due to bankruptcy, mergers, firms going private, etc. We can deal with this issue in two different ways: either we do not consider these firms or we impute an actual earnings figure to them. In the first case, we may be biasing severely the sample towards firms that survived. To avoid this problem, we use the second alternative. Our rationale for the imputation of earnings follows Chan, Karceski and Lakonishok (2003). We take the liquidation value of the stock and apply it into the market portfolio. So we assume that firms that are delisted would have an earnings/price ratio (where the price is the liquidation price) the same as that of the value-weighted market portfolio. For the current year, the number of imputations made is 53, excluding imputations, the number of observations is 47,220; For the fifth year, the number of imputations made is 7,765, while excluding imputations, the number of observations is 27,240. In terms of market capitalization, the effect of the imputation on the current year is minimal (less than 1%), while the imputation increased the market capitalization by 12.7% for the fifth year.

3 Adjusting analyst forecasts

3.1 Adjusting for special items

We define the forecast error as the actual earnings minus analyst earnings forecast. We take actual earnings from Compustat and earnings forecast from I/B/E/S.

Philbrick and Ricks (1991) point out that write-downs and write-offs (as well as other special accruals) are sometimes considered by I/B/E/S as extraordinary items, while by generally accepted accounting principles they are not considered as such. If this is the case, the analysts surveyed by I/B/E/S in fact forecast earnings before extraordinary and other specific items. It is not always easy to determine what specific items are left out. As I/B/E/S puts it: "With very few exceptions analysts make their earnings forecasts on a continuing operations basis. This means that I/B/E/S receives an analysts forecast after discontinued operations, extraordinary charges, and other non-operating items have been backed out. While this is far and away the best method for valuing a company, it often causes a discrepancy when a company reports earnings." (I/B/E/S, 2000 Glossary, page 8.)

Therefore, we assume:

Assumption 1: *Analysts forecast earnings before discontinued operations, extraordinary and special items. That is, they forecast Compustat data item*

20 −(data item 17)×(1- tax rate).

Here the special items (Compustat data item 17) variable is reported before taxes. To make it comparable with earnings (which is after tax), we need to adjust special items for taxes. So if pretax income from Compustat (item 170) is positive and bigger than special items, we define effective tax rate as the ratio of income taxes (item 16) to pretax income, up to a maximum of 40%. For all other cases, the tax rate is set to zero.

Formally, if we define EX as the earnings per dollar before discontinuing operations and extraordinary items, E as the earnings per dollar before discontinuing operations, extraordinary and special items (SI), (that is, $EX = E + SI$.) and F as the earnings analysts forecast per dollar, then the forecast errors for firm i in year t are respectively:

$$\begin{aligned} FEX_{it} &= EX_{it} - F_{it} \\ FE_{it} &= E_{it} - F_{it} \end{aligned}$$

Note that a negative forecast error means the forecast is optimistic. Our discussion above suggests that the literature generally uses FEX as the forecast error, while we propose to use FE instead.

Assuming analysts' goal is to minimize the Mean Square Forecast Error, then Assumption 1 implies:

$$\begin{aligned} E(FE_{it}) &= 0, \\ E(FEX_{it}) &= SI_{it} \neq 0. \end{aligned} \tag{1}$$

Under Assumption 1, if one does not take into consideration special items, forecasts will be biased. In particular, if on average special items are negative one would erroneously consider the average forecast as "optimistic." We believe this can potentially explain the general view that analysts forecasts are optimistic. In Figure 1.1 one can see that there is an almost one-to-one relation between the forecast error FEX and special items, as prescribed in (1). It is as if special items were the only necessary explanation for the bias in the forecasts identified by the literature. In Figure 1.2 we plot the relation between FE and SI, and in this case there is no important relation between forecast errors and special items. Table 3 confirms these results. The effect of factoring out special items is striking! The "uncorrected" forecast error – FEX – is on average negative (around 30% of actual earnings EX), pointing to the well-documented optimism. But if one uses instead the earnings before extraordinary and special items, the average FE is only 7% of these earnings, E. Moreover, the standard deviation of the forecast error drops by 40%, confirming that this is an important and useful correction.

For future reference, we denote the analyst forecast without taking out special items as AUF (Analyst Unadjusted Forecast), and the adjusted forecast adjusted by taking out special items as AAF1 (version 1 of Analyst Adjusted Forecast).

3.2 Adjusting for analyst underreaction to public information

One empirical regularity found in the literature is the systematic underreaction of analysts to publicly available information. (The earlier studies are Brown and Rozeff (1979), Mendenhall (1991), Abarbanell and Bernard (1992), Jacob and Lys (1992), Ali et al. (1993).) Underreaction means that analysts under-adjust their forecasts to current available public information. So if analysts were too optimistic about last year earnings for a certain firm, they will probably be optimistic also this year (i.e., positive autocorrelation in the forecast error).

To take into account of the serial correlation in analyst forecasting error, we truncate the auto-correlation in the error to two lags. The results are insensitive to how many lags to keep. Specifically, to get the auto-correlation coefficients to adjust the forecasts in year t, we run the following regression:

$$FE_{i\tau} = \theta_{0t} + \theta_{1t} FE_{i,\tau-1} + \theta_{2t} FE_{i,\tau-2} + \epsilon_{i,\tau} \quad \text{where } \tau < t \tag{2}$$

over all available firms in the portfolio under study and over all the years before year t, where FE is the analyst forecast error after taking out Special Items (AAF1).

We then construct version 2 of the analyst adjusted forecasts ($AAF2$) as:

$$\begin{aligned} AAF20_{it} &= AAF10_{it} + \hat{\theta}_{0t} + \hat{\theta}_{1t} FE_{i,t-1} + \hat{\theta}_{2t} FE_{i,t-2} \\ AAF21_{it} &= AAF11_{it} + \hat{\theta}_{0t} + \hat{\theta}_{1t} FE_{i,t-1} + \hat{\theta}_{2t} FE_{i,t-2} \\ AAF24_{it} &= AAF21_{it} \times (1 + lwlrg_{it})^3 \end{aligned}$$

We use a minimum of five years to run each regression. (We included earnings and forecasts data between 1976 and 1981 in order to be able to implement the AAF2 for our period which starts in 1982.) Remember that each year has a large cross section of data. Notice that for AAF24, we use the lowest long-run EPS growth forecasts (lwlrg) instead the concensus EPS growth forecasts (lrg). This is because researches have found that the concensus long-run EPS growth is way too optimistic.

3.3 Earnings time series forecast (TSF)

Many studies in the accounting literature have compared the performance of analyst forecasts and time series forecasts. For reference, we also present the results of time series forecasts at portfolio levels.

For every year t in our sample, 1982-2001, we first run the following regression, using data going as back as 1976 upto year $t-1$ (so we are using an expanding window to perform the regression):

$$epd_{i\tau} = \alpha_{\nu t} + \beta_{\nu t}\, epd_{i,\tau-\nu} + u_{i,\tau}, \quad \text{where } \tau < t \text{ and } \nu = 1, 2, 5. \tag{3}$$

for all firms with available data in the portfolio under consideration. Here *epd* is the earnings per dollar after taking out Special Items. Then, we use the estimated parameters to construct the following forecasts:

$$\begin{aligned} TSF0_{it} &= \hat{\alpha}_{1t} + \hat{\beta}_{1t}\, epd_{i,t-1} \\ TSF1_{it} &= \hat{\alpha}_{2t} + \hat{\beta}_{2t}\, epd_{i,t-1} \\ TSF4_{it} &= \hat{\alpha}_{5t} + \hat{\beta}_{5t}\, epd_{i,t-1} \end{aligned}$$

Note that we use at least five years of data to run each regression and each year carries a large cross section of data.

3.4 Accuracy of alternative earnings forecasts

We now evaluate the accuracy of the alternative earnings forecasts described above. We will examine the summary statistics of both forecast errors and absolute forecast errors.

Table 4 presents the summary statistics for the forecast errors of alternative earnings forecasts. Several points are worth mentioning. First, there is clear sign of general optimism (i.e., negative forecasting error) of the unadjusted analyst forecasts (AUF). This is consistent with the existing literature on the properties of analyst earnings forecast. Furthermore, for the unadjusted analyst forecasts, the further into the future of the forecasting horizon, the more optimistic the forecasts are, when optimism is measured as the forecast error as a percentage of the realized earnings. For the current fiscal year, the percentage forecast error is 14.34% (= 0.98/6.79). The percentage forecast error increased to 23.57% (= 1.81/7.68) for the next fiscal year, and 35.44% (= 4.15/11.71) for three years after that. Also, version 1 of the analyst adjusted forecasts (AAF1) also shows general optimism, although it is significantly attenuated. This means special items cannot account for all the analyst optimism.

Second, for all levels of analysis and at all three forecasting horizons, AAF1 and AAF2 have smaller forecasting error than AUF. AAF2 also beats TSF. Overall, AAF2 is has the smallest forecast error.

Table 5 presents summary statistics for the absolute forecast error (AFE). The table generally confirms the results from the previous one. AAF1 and AAF2 beat the other two forecasts. And they are comparable to each other. Compare to Table 4, we see that considering the serial correlation structure of forecast errors reduces mean forecast error, but does little in reducing the mean absolute forecast error. This may be because we have to estimate the parameters in the serial correlation structure in the forecasting error when constructing AAF2. The sampling errors in the parameter estimates may increase the dispersion of the forecasts of AAF2.

Tables 4 and 5 show that analysts (unadjusted) forecasts of growth rates are not very useful per se. In particular, long run growth rates based on time series are easily better forecasts than the analysts (unadjusted) counterparts. This is important because many previous researches that uses analyst forecasts without adjustment. Examples include Claus and Thomas (2001), Gebhardt, Lee and Swaminathan (2001), and Frankel and Lee (1998).

In the tables that follow, we divide the overall sample into two classes of six portfolios. In the first class we partition the sample into two market size portfolios and three momentum portfolios. In the second, we use the market size portfolios plus three book-to-market portfolios.[2] Table 6 shows the results.

Several patterns emerge from Table 6. First, consider the difference in earnings of different portfolios. Panel A shows that earnings for losers, whether large or small, are significantly depressed than earnings for winners. On the other hand, along the size dimension, small losers earn much less than large losers, but small winners earn more than large winners. This asymmetric pattern is not present for the book-to-market portfolios in Panel B: earnings of small growth firms are not much different from those of large growth firms, and the same is true for value stocks. But growth firms, whether large or small, earn less than value stocks.

Second, consider the difference in unadjusted analyst forecast error. We see that analysts forecasts are the most optimistic for small/loser stocks. The next groups are small/value and small/growth stocks and large/loser stocks. On the other hand, both small/winners and large/winners as well as large/value and large/growth stocks show less analyst optimism.

This pattern in analyst optimism is similar (in some aspects) to the investor optimism as postulated in the behavioral explanation of equity return

[2]The construction of all portfolios was explained before, in Section 2.

anomalies. For example, the behavioral explanation of the momentum phenomenon is that investors are too optimistic about loser stocks, hence they bid up the stock prices too high and the stocks future returns will be lower than the other stocks. For analysts forecasts, we see that analysts are also too optimistic about losers.

On the other hand, if we think that it takes time for investors bid up the stock prices too high, then the behavioral explanation does not accord well with the fact that these stocks (the losers) did not perform well in the past.

Also, one explanation of the systematically biased expectation is that investors extrapolate past performances too far into the future (LSV(1996), La Porta (1994)). But the earnings of small/losers are depressed, hence if investors extrapolate the firms' past performance, they should be pessimistic about these firm, not optimistic.

The forecast error of AAF1, which assumes that analysts are forecasting earnings excluding Special Items, shows similar pattern as, though less optimism than, the Analyst Unadjusted Forecasts (AUF). In particular, the analyst optimism is the most severe for small/loser stocks and small/growth stocks.

Not surprisingly, AAF2, which is based on AAF1 but takes into account of the mean and serial correlation in forecasting errors, shows much less bias and also there is little systematic variations in analyst optimism across different portfolios.

Our results show that analyst bias vary systematically with firm charactersitcs. However, this bias can be corrected to a large extent rather easily. Not only the adjusted forecast are almost unbiased overall, but also they do not show systematic variations in bias with firm characteristics. With the ease of correcting the analyst forecasts, we would expect that analyst bias should be easily factored in the stock prices by investors. We examine this issue in the next section.

4 Firm characteristics, analyst optimism, and future stock returns

Researchers have documented various equity return anomalies. One line of explanation for these return anomalies is that investors are not perfectly rational. They tends to be too optimistic about certain class of stocks and bid the stock prices too high. Over time the fair values of the stocks are gradually revealed and the stock prices regress to their fair values, resulting a lower return for these stocks in the future. Investors can also be too pessimistic about other stocks and resulting in higher future returns for these stocks.

This explanation has two implications. First, investors optimism/pessimism vary systematically with firm characteristics; Second, investor optimism/pessimism can predict future stock returns. Because analysts and investors are exposed to much of the same information, we expect to find the same two empirical regularities with analyst (instead of investor) optimism/pessimism. (La Porta (1996) and La Porta *et al.* (1997) also examine whether analyst forecast of long run earnings growth is related to future stock returns. Our method is different – see the details below.) In this section we examine the empirical regularity in these two aspects.

Our empirical results in the last section seem to confirm that analysts optimism vary systematically with firm characteristics: We found that analysts are most optimistic in their earnings forecast about small/loser and small/growth stocks, and these stocks earn lower future returns as documented by existing studies. But the result in Table 6 does not give statistical significance about these variations.

In order to gauge the statistical significance of the systematic variation of analyst optimism with firm characteristics, we perform a Fama-MacBeth-type regression analysis. First, we perform the following cross-sectional regression each year. The dependent variable is a measure of analyst optimism, and the independent variables are dummy variables indicating firms' characteristics along various dimensions such as size, book-to-market, etc. Then we analyze the time series of the regression coefficients and determine their statistical significance using Fama-MacBeth approach, where we calculate the (time-series) standard errors of the coefficients using the Newey-West estimator allowing for two leads and two lags. (Increasing the number of leads and lags allowed to three or four gives qualitatively the same results.)

We use two measures of analyst optimism. The first is the analyst forecast error of current year's earnings per dollar, which is the actual earnings minus earnings forecast. The second is the analyst long-run EPS growth rate forecast. Both measures are analyst unadjusted forecasts (AUF). Chan et al. (2003) document that analyst long-run EPS growth rate forecast has little correlation with the actual realized EPS growth rate in the future. Hence the long-run EPS growth rate forecast is a measure of analyst optimism.

We use the following firm characteristic dummy variables (they take values of either zero or one). (1) DlowNoEst: denote the number of analysts following the stock is low. It takes the value of one if the total number of current year earnings forecasts, next year earnings forecasts, and long-run EPS growth rate forecasts are less than or equal three.

(2) Dwinner, Dloser, and Dother: Here we follow Jegadeesh and Titman's (1993, 2001) definition of winners and lowers. Each month, all stocks traded on the New York Stock Exchange (NYSE) and American Stock Exchange, with prices greater than or equal to $1.00 at the time of portfolio formation, are ranked according to the past twelve months' total return and assigned to five quintiles. "Winners" and "losers" are the top and bottom quintiles, respectively. All NASDAQ stocks or stocks with price less than $1.00 are in the "other" group.

(3) Dvalue and Dgrowth: We follow Fama and French (1992, 1993) to determine value and growth stocks. First, NYSE stocks are ranked at the end of June into five quintiles according to book-to-market equity. We exclude firms with negative book equity when determining the quintile breakpoints. A stock (could be a AMEX stock or a NASDAQ stock) is denoted a value or growth stock if its book-to-market equity ratio is in the top or bottom NYSE book-to-market quintiles, respectively.

(4) Dbig and Dsmall: In the end of June, we rank all NYSE stocks in terms of market capitalization (price times shares) into quintiles. A stock (could be an AMEX stock or a NASDAQ stock) is denoted a big or small stock if its size is in the top or bottom NYSE size quintiles.

(5) DhighTurnover and DlowTurnover: We follow Lee and Swaminathan (2000) and Jiang, Lee, and Zhang (2004). Each month, we rank common domestic stocks which are traded on the NYSE, AMEX, and NASDAQ according to the average daily turnover over the past 12 months. The daily turnover is the ratio of number of shares traded over the total shares outstanding at the end of day. We rank NASDAQ stocks separately from NYSE and AMEX stocks because trading volume on NASDAQ is inflated relative

to NYSE/AMEX stocks due to double counting of dealer trades (Gould and Kleidon (1994)). The high turnover and low turnover stocks are those in the top and bottom quintiles in terms of average daily turnover, respectively.

Other papers that document that turnovers predict future returns include Brennan et al. (1998), who interpret this as liquidity premium – more liquid stocks earn less. Datar, Naik, and Radcliffe (1998) and Lee and Swaminathan (2000) find that firms with high (low) past turnover ratios exhibit many glamour (value) characteristics and earn lower future returns. Also, Chordia et al. (2001) find a strong negative cross-section relation between stock returns and the variability of dollar trading volume and share turnover, after controlling for size, book-to-market, momentum, and the level of dollar volume and share turnover. Baker and Stein (2004) interpret this as sentiment – when trading volume goes up for a stock in time, it is followed by lower return.

There are also theoretical papers, such as Campbell, Grossman, and Wang (1993) and Blume, Easley, and O'Hara (1994), suggest that past trading volume may provide valuable information about a security's return.

(6) DhighAccruals and DlowAccruals: We follow Hirshleifer et al. (2004) in calculating accruals. See their paper for the details. Again each year we rank the firms according to their accruals and denote the top and bottom quintiles as high accruals and low accruals firms, respectively.

Sloan (1996) documents that firms with high working capital accruals subsequently underperform firms with low working capital accruals, both in terms of earnings and in terms of stock returns.

Recall that the time of our analysis is nine months before the end of the fiscal year. The values of the above dummy variables are their prevailing values at that time.

Tables 7 and 8 report the Fama-MacBeth regression results. In Table 7, the dependent variable is this fiscal year's forecasting error of earnings per dollar (EPD). Table 7 shows that analysts are more optimistic for firms with less analysts following; for loser stocks; for value stocks; for small stocks; for stocks with high turnover; for stocks with both high and low accruals. These results accord well with the behavioral explanation of equity return anomalies in some respects: loser stocks, small stocks, stocks with high turnover, and stocks with high accruals tend to have lower future returns, and the explanation is that investors are over-optimistic about such stocks. However, for value vs. growth stocks, our result is the opposite of the behavioral explanation: growth stocks tend to have lower returns yet analysts are less optimistic about them than about value stocks. Also, we find analysts are more optimistic about firms with low accruals as well as high accruals.

Table 8 reports the results when the dependent variable is the long-run EPS earnings forecasts. We see that analysts are more optimistic about winner stocks, stocks which are neither winner nor loser, growth stocks, small stocks, stocks with high turnover, and stocks with either high accruals or low accruals. On the other hand, they are more pessimistic about value stocks, big stocks, and stocks with low turnovers. By and large, these results accord well with the behavioral explanation of equity return anomalies.

Table 7 and 8 show that analysts optimism vary systematically and significantly with firm characteristics. They show that analysts seem to exhibit the same optimism as investors do as postulated by the behavioral explanation of equity return anomally.

The next empirical question we examine is whether analysts optimism can predict future stock return. We again use the Fama-MacBeth method to examine this question. Here the average monthly return of the next 12 months is the dependent variable. The independent variables are measures of analyst optimism and firm characteristics which serve as controls. Because we want the investors to be able to trade on measures of optimism, our analyst optimism measures are (1) current long-run EPS growth rate forecasts; (2) last year's forecast error of earnings per dollar. We include the second measure because analyst forecast error are positively serially correlated, hence last year's forecast error is a valid measure of current analyst optimism. Both measures are analyst unadjusted forecasts (AUF).

Table 9 shows the result. The first column shows that stocks with high long-run EPS growth rate forecast tend to have lower average monthly return over the next twelve months, but only by 39 basis points.

The second column shows that last year's forecast error does not indicate superior or inferior future stock returns at all.

The third column shows that the usual firm characteristics can predict future stock return to some extent, and the results are largely consistent with those in the extant studies. For example, winners and value stocks have higher future return, while stocks with high turnover or high accruals have lower future return. The magnitude of these return differentials are somewhat smaller than those documented in the existing literature. This is because we require the firms to be covered by I/B/E/S, hence they tend to be larger and more liquid stocks.

Column 4 of Table 9 shows that, when firm characteristics such as size, book-to-market, etc., are controlled for, neither measure of analyst optimism can predict future stock returns at one year horizon.

Table 10 is the same as Table 9 except the independent variable is the total return over the next twelve months after the portfolio formation. The first column shows that high analyst expected long-run EPS growth rates implies lower future returns, but by only 5 percent and is only marginally significant at best (t-value is -1.60). The second column shows that previous year's analyst forecast error has no prediction of next year's stock return at all. Column three shows that firm characteristics can predict future return, and the pattern as similar to those documented in the existant literature. Column four shows that controlling for firm characteristics, both measures of analyst optimism cannot predict future stock returns. The result in Table 9 and Table 10 are qualitatively similar.

5 Conclusion

`Need to be done.`

REFERENCES

Abarbanell, Jeffery S., and Reuven Lehavy, 2003, Biased Forecasts or Biased Earnings? The Role of Reported Earnings in Explaining Apparent Bias and Over/Underreaction in the Analysts Earnings Forecasts, *Journal of Accounting and Economics* 36, 105-146.

Abarbanell, Jeffery S., and Reuven Lehavy, 2002, Differences in Commercial Database Reported Earnings: Implications for Inferences Concerning Analyst Forecast Rationality, the Association between Prices and Earnings, and Firm Reporting Discretion, University of North Carolina and University of Berkeley, Working Paper.

Abarbanell, Jeffery S., 1991, Do Analysts Earnings Forecasts Incorporate Information in Prior Stock Price Changes?, *Journal of Accounting and Economics* 14, 147-165.

Ali, A., A. Klein, and J. Rosenfeld, 1993, Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS, *Accounting Review* 67, 183-198.

Baker, Malcolm, and Jeremy C. Stein, 2004, Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7, 271-299.

Bauman, Victor L., and Richard Dowen, 1988, Growth projections and common stock returns, *Financial Analysts Journal*, July-August, 79-80.

Bernard, Victor L., and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27 (supplement), 1-36.

Blume, Lawrence, David Easley, and Maureen O'Hara, 1994, Market statistics and technical analysis: The role of volume, *Journal of Finance* 49, 153-181.

Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics* 49, 345-373.

Brown, Lawrence D., and Jerry C. Y. Han, 2000, Do stock Prices Fully Reflect the Implications of Current Earnings for Future Earnings for AR1 Firms?, *Journal of Accounting Research* 38, 149-164.

Brown, Lawrence D., Robert L. Hagerman, Paul A. Griffin, and Mark E. Zmijewski, 1987, Security Analyst Superiority Relative to Univariate Time-Series Models in Forecasting Quarterly Earnings, *Journal of Accounting and Economics* 9, 61-87.

Brown, L, and M. Rozeff, 1979, Univariate time series models of quarterly accounting earnings per share: A proposed model, *Journal of Accounting Research* 17, 179-189.

Blanchard, Olivier J., 1993, Movements in the Equity Premium, *Brooking Paper on Economic Activity* 2, 75-138.

Campbell, John Y., 1991, A Variance Decomposition for Stock Returns, *Economic Journal* 101, 157-179.

Campbell, John Y., Sanford J. Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 107, 905-939.

Campbell, John Y., and Robert J. Shiller, 1988, The Dividend Price Ratio and Expectations of Future Dividends and Discount Factors, *Review of Financial Studies* 1, 195-227.

Chan, Louis K. C., Jason Karceski and Josef Lakonishok, 2003, The Level and Persistence of Growth Rates, *Journal of Finance* 58, 643-684.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1999, The profitability of momentum strategies, *Financial Analysts Journal*, November/December, 80-90.

Chan, Wesley S., Richard Frankel, and S. P. Kothari, 2003, Testing behavioral finance theory using trends and sequences in financial performance, *working paper,* Sloan School of Management, MIT.

Chordia, Tarun, Avanidhar Subrahmanyam, and V. Ravi Anshuman, 2001, Trading activity and expected stock returns, *Journal of Financial Economics* 59, 3-32.

Claus, James, and Jacob Thomas, 2001, Equity Risk Premia as Low as Three Percent? Evidence from Analysts Earnings Forecasts for Domestic and International Stock Markets, *Journal of Finance* 56, 1629-1665.

Cochrane, John, 1992, Explaining the Variance of Price-Dividend Ratios, *Review of Financial Studies* 15, 243-280.

Datar, Vinay, Narayan Naik, and Robert Radcliffe, 1998, Liquidity and asset returns: An alternative test, *Journal of Financial Markets* 1, 203-220.

Dechow, P.M., and Richard G. Sloan, 1997, Returns to contrarian investment strategies: Tests of naive expectations hypothesis, *Journal of Financial Economics* 43, 3-27.

Diebold, Francis X., and Roberto S. Mariano, 1995, Comparing Predictive Accuracy, *Journal of Business and Economic Statistics* 13, 253-263.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Return, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1995, Size and Book-to-Market Factors in Earnings and Returns, *Journal of Finance* 50, 131-155.

Fama, Eugene F., and Kenneth R. French, 2002, The Equity Premium, *Journal of Finance* 57, 637-659.

Fama, Eugene F., and James MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy* 71, 607-636.

Francis, Jennifer and Donna Philbrick, 1993, Analysts' Decisions as Products of a Multi-Task Environment, *Journal of Accounting Research* 31, 216-230.

Frankel, Richard, and Charles M. C. Lee, Accounting valuation, market expectation, and cross-sectional stock returns, *Journal of Accounting and Economics* 25, 283-319.

Gebhardt, William R., Charles M. C. Lee, and Bhaskaram Swaminathan, 2001, Toward an Implied Cost of Capital, *Journal of Accounting Research* 39, 135-176.

Givoly, Dan, and Josef Lakonishok, 1979, The information content of financial analysts' forecasts of earnings: Some evidence on semi-strong inefficiency, *Journal of Accounting and Economics* 1, No. 3, 165-185.

Gordon, Myron, 1962, *The Investment Financing and Valuation of the Corporation*, Irwin: Homewood, IL.

Gould, John F., and Alan W. Kleidon, 1994, Market maker activity on Nasdaq: Implications for trading volume, *Stanford Journal of Law, Business and Finance* 1, 1-17.

Gu, Zhaoyang, and Joanna Shuang Wu, 2003, Earnings Skewness and Analyst Forecast Bias, *Journal of Accounting and Economics* 35, 5-29.

Guay, Wayne R., S. P. Kothari, and Susan Su, 2003, Properties of implied of cost of capital using analysts' forecasts, *working paper* 4422-03, MIT Sloan School of Management.

Hamilton, James, 1994, *Time series Analysis*, Princeton University Press, Princeton, NJ.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets? *working paper*, Fisher College of Business, Ohio State University.

Jacob, John, and Thomas Lys, 1992, Determinants and Implications of the Serial-Correlation in the Analysts Earnings Forecast Errors, Working paper, Northwestern University.

Jagannathan, Murali, Clifford P. Stephens and Michael S. Weisbach, 2000, Financial Flexibility and the Choices between Dividends and Stock Repurchases, *Journal of Financial Economics* 57, 355-384.

Jagannathan, Ravi, Ellen R. McGrattan, and Anna Scherbina, 2000, The Declining U.S. Equity Premium, *Federal Reserve Bank of Minneapolis Quarterly Review* 24(4), 3-19.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65-91.

Jiang, Guohua, Charles M. C. Lee, and Grance Y. Zhang, 2004, Information uncertainty and expected returns, *working paper*, Johnson Graduate School of Management, Cornell University.

Keane, Michael P., and David E. Runkle, 1998, Are Financial Analysts Forecasts of Corporate Profits Rational?, *Journal of Political Economy* 106, 768-805.

Kothari, S. P., Jonathan Lewellen, and Jerold B. Warner, 2004, Stock returns, aggregate earnings surprises, and behavioral finance, *working paper*, Sloan School of Management, MIT.

La Porta, Rafael, 1996, Expectations and the Cross-Section of Stock Returns, *Journal of Finance* 51, 1715-1742.

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert Vishny, 1997, Good News for Value Stocks: Further Evidence on Market Efficiency, *Journal of Finance* 52, 859-874.

Lakonishok, Josef, Andrei Shleifer, and Robert Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance* 49, 1541-1578.

Latane, Henry A., and Charles P. Jones, 1979, Standardized unexpected earnings–1971-77, *Journal of Finance* 34, 717-724.

Lee, Charles, and Bhaskaran Swaminathan, 2000, Price Momentum and Trading Volume, *Journal of Finance* 55, 2017-2069.

Mehra, Rajnish, and Edward Prescott, 1985, The Equity Premium: A Puzzle, *Journal of Monetary Economics* 15, 145-161.

Mickail, Michael B., Beverly R. Walther, and Richard H. Willis, 2001, The Effect of Experience on Security Analyst Underreaction and Post-Earnings-

Announcement Drift, Working paper, Kellogg Graduate School of Business, Northwestern University.

Mickail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999, Does Forecast Accuracy Matter to Security Analysts?, *The Accounting Review* 74, 185-200.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

Philbrick, Donna R., and William E. Ricks, 1991, Using Value Line and I/B/E/S Analyst Forecasts in Accounting Research, *Journal of Accounting Research* 29, 397-417.

Revsine, Lawrence, Daniel W. Collins, and W. Bruce Johnson, 1998, *Financial Reporting and Analysis,* Prentice-Hall, Inc., New Jersey.

Schipper, K., 1991, Commentary on Analysts Forecasts, *Accounting Horizons* 5 (December), 105-121.

Sloan, R.G. 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? *The Accounting Review* 71, 289-315.

Table 1 - Sample description

Panel A compares the number of observations and market capitalization (as a percentage of CCM) under alternative samples. CCM stands for CRSP/COMPUSTAT Merged and represents the analogous to the Fama and French (1992) sample. We require an observation to have valid and positive book equity and market equity (so can be assigned to a size and a book-to-market decile portfolio) and valid monthly return from month t-12 to month t-1 (so can be assigned to a momentum decile portfolio). CCIM is CCM merged with I/B/E/S data. We require an observation to have at least one valid forecast value of the following: the EPD of upcoming fiscal year, the EPD of the next fiscal year, or the long-run earnings forecast. In the last row of Panel A, we clean CCIM by deleting some of the observations (See panel B for details). This is the sample we use through out the paper and we call the sample CCIMC. Panel A also presents the Mean and Standard Deviation of Earnings per Dollar (EPD) and Forecast Error (EPD – median earnings forecast) for FY0 from the CCIM sample before and after the cleaning process. The values presented are valued-weighted using current market capitalization. Panel B details the criteria used to clean CCIM as well as the number of observations deleted under each criteria. All statistics are valued-weighted. The sample is from January 1982 to December 2001. See text for additional details.

Panel A: Composition and Comparison of Samples

Sample	Observations	% of CCM Market Capitalization	Earnings Per Dollar FY0		Forecast Error FY0	
			Mean	STD	Mean	STD
CCM	77,853	100.00				
CCIM	49,225	98.33	0.0580	0.1097	-0.0131	0.0990
CCIM Cleaned	47,283	95.94	0.0617	0.0729	-0.0097	0.0599

Panel B: Cleaning Criteria

CRITERIA	NUMBER OF OBSERVATIONS DELETED
Ex-Ante Outliers:	
Absolute Value of lagged EPD bigger than 1	126 observations deleted
Absolute Value of EPD FY0 bigger than 1	21 observations deleted
Absolute Value of EPD FY1 bigger than 1	3 observations deleted
No value for variables needed:	
No observation for EPD	26 observations deleted
Extreme values for:	
EPD FY0 (top and bottom 0.5%)	434 observations deleted
Lagged Forecast Error (top and bottom 0.5%)	408 observations deleted
Return of last 12 months (top and bottom 0.5%)	549 observations deleted
Standard deviation of Consensus forecast (top 1%)	375 observations deleted

Panel C: Number of Missing Values of CCIM Cleaned

Variable	Number of Missing Values
Forecast of EPD FY0	95
Forecast of EPD FY1	14,626
Long-run growth of earnings forecast	8,955

Table 2 – Number of Observations per Portfolio

This table compares the number of observations per portfolio for the initial sample (very close to the Fama and French (1992) sample) with those from the sample we are using (CCIM cleaned). The sample period is January 1982 to December 2001.

		Momentum Portfolios			Book-to-Market Portfolios		
Sample	**Size Portfolios**	**Losers**	**Medium**	**Winners**	**Low**	**Medium**	**High**
CCM	**Small**	25,856	17,617	17,936	20,239	19,719	21,451
	Large	3,901	7,268	5,249	7,257	6,143	3,018
CCIM Cleaned	**Small**	11,625	10,304	9,602	10,680	11,819	9,032
	% CCM	45%	58%	54%	53%	60%	42%
	Large	3,633	7,087	5,050	6,970	5,943	2,857
	% CCM	93%	98%	96%	96%	97%	95%

Table 3 – Summary Statistics for Earnings and Forecast Error under Different Definitions

The table presents earnings per dollar before extraordinary items (EX) and before extraordinary and special items (E). SI stands for special items per dollar. FEX and FE are respectively the forecast error (actual –forecast) when the actual earnings used are EX and E respectively. To obtain values per dollar we divide values per share by its price 12 months before. From our sample of CCMIC, we delete observations for which special items were either zero or not available, resulting in a sample size of 18,305. All statistics are valued-weighted. The sample period is January 1982 to December 2001. See text for additional details.

Variable	**Number of Observations**	**Mean**	**Standard Deviation**
EX	18,305	.0483	.0799
E	18,305	.0597	.0576
SI	18,305	-.0113	.0609
FEX	18,254	-.0157	.0706
FE	18,254	-.0044	.0419

Table 4 – Summary Statistics of the Earnings Forecast Error in the Overall Sample

The table presents summary statistics for the actual Earnings per Dollar (EPD) and the Forecast Error (Actual EPD – Forecasted EPD) under the alternative forecasts (AUF, AAF1, AAF2, TSF). AUF involves no adjustment at all; AAF1 takes out Special Items in earnings when calculating forecast error, and AAF2 is based on AAF1 but also takes into account of the serial correlation in forecasting errors. TSF is the time series forecast. The statistics are shown for the current fiscal year (FY0), next fiscal year (FY1) and four years after the current fiscal year (FY4). All values are multiplied by 100. The sample period is January 1982 to December 2001. See text for additional details.

	FY0			**FY1**			**FY4**		
	Mean	**Median**	**Std Dev**	**Mean**	**Median**	**Std Dev**	**Mean**	**Median**	**Std Dev**
Earnings per Dollar	6.79	6.36	5.93	7.68	7.09	7.48	11.71	10.74	15.29
Forecast Error AUF	-0.98	-0.16	6.01	-1.81	-0.66	7.93	-4.15	-3.20	79.00
Forecast Error AAF1	-0.35	-0.06	4.24	-0.92	-0.37	6.10	-2.60	-2.52	13.65
Forecast Error AAF2	0.07	0.30	4.19	-0.48	0.05	6.11	-0.42	-0.46	13.73
Forecast Error TSF	-1.22	-1.54	5.05	-1.27	-1.81	7.29	1.26	-0.15	12.83
No. of Observations		47,184			30,623			21,323	

Table 5 – Summary Statistics for Earnings Absolute Forecasts Error in the Overall Sample

The table presents summary statistics for the Absolute Forecast Error (AFE). The forecasts under consideration are the Analysts Unadjusted Forecasts (AUF); the Analysts Adjusted Forecasts: AAF1 only takes out the Special Items, AAF2 also takes into account of the serial correlation in forecast errors; and the Time Series Forecast (TSF). Results are shown for the current fiscal year (FY0), next fiscal year (FY1) and four years after the current fiscal year (FY4). Each observation represents a firm year. All values are multiplied by 100. The sample period is January 1982 to December 2000. See text for additional details. See Table 4 for additional statistical properties.

	FY0		**FY1**		**FY4**	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
AUF	2.35	0.86	3.79	1.74	7.90	4.90
AAF1	1.71	0.62	3.01	1.44	6.97	4.37
AAF2	1.77	0.77	2.99	1.39	6.54	3.86
TSF	2.89	1.99	4.11	2.78	6.62	4.01
No.of Observations	47,338		30,672		17,937	

Table 6 – Summary Statistics of the Earnings Forecast Error for Different Portfolios

The table presents the summary statistics for the earnings per dollar and the forecast error, defined as actual minus forecasted earnings per dollar. To obtain values per dollar we divide values per share by its price 12 months before. The forecasts under consideration are the AUF, which involves no adjustment at all; AAF1, which takes out the Special Items; AAF2, which is based on AAF1 but also takes into account of the serial correlation in forecasting error; and the Time Series Forecast (TSF). Results are shown for the current fiscal year (FY0), next fiscal year (FY1) and four years after the current fiscal year (FY4). We analyze six portfolios based on size and momentum and other six ones based on size and book to market. All values are multiplied by 100. The sample period is January 1982 to December 2000. Each observation represents a firm year. See text for additional details.

	FY0		FY1		FY4		FY0		FY1		FY4		FY0		FY1		FY4	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Panel A. Market Size / Market Momentum Portfolios																		
	SMALL\ LOSERS						**SMALL\ MEDIUM**						**SMALL\ WINNERS**					
Earnings per Dollar	1.9	12.6	3.6	12.3	7.3	14.1	7.3	8.7	7.7	11.5	11.8	16.5	9.5	12.2	9.3	17.2	18.2	27.0
Forecast Error AUF	-5.6	18.0	-5.7	15.7	-6.3	17.5	-2.1	9.7	-3.2	13.2	-5.8	20.7	-1.4	14.8	-4.5	23.0	-6.0	35.6
Forecast Error AAF1	-3.6	11.5	-3.5	11.9	-4.8	14.7	-1.1	7.3	-2.0	11.0	-3.5	16.6	-0.2	9.7	-2.2	16.1	-2.6	26.6
Forecast Error AAF2	1.1	11.3	0.9	12.0	3.3	15.3	-0.1	7.2	-1.0	10.9	-1.1	16.6	-0.4	9.5	-2.3	16.0	-1.6	26.9
Forecast Error TSF	0.5	11.5	2.5	11.9	6.3	14.1	-1.0	8.0	-1.0	11.4	1.2	16.6	-0.8	10.2	-2.7	17.0	4.0	27.3
Observations	11,574		5,598		2,520		10,333		5,463		2,656		9,627		5,653		2,472	
	LARGE\ LOSERS						**LARGE\ MEDIUM**						**LARGE\ WINNERS**					
Earnings per Dollar	4.4	5.4	5.9	6.5	8.9	10.6	6.8	4.4	7.6	5.5	10.9	9.3	7.6	5.8	8.3	7.1	13.8	13.2
Forecast Error AUF	-2.3	5.3	-3.0	8.2	-4.5	12.2	-1.1	4.2	-1.8	6.1	-3.6	10.4	-0.1	5.1	-1.2	7.0	-3.2	14.1
Forecast Error AAF1	-1.2	4.0	-1.9	6.1	-3.0	11.0	-0.5	3.3	-1.0	5.0	-2.6	9.1	0.2	3.6	-0.4	5.4	-2.1	12.6
Forecast Error AAF2	0.6	4.3	-0.1	6.4	0.9	11.2	0.0	3.3	-0.5	5.0	-0.5	9.2	-0.4	3.6	-1.0	5.4	-1.6	12.7
Forecast Error TSF	-1.4	4.7	-0.4	6.4	1.2	10.6	-1.3	3.9	-1.0	5.7	0.7	9.2	-1.7	4.9	-2.4	6.9	0.6	13.6
Observations	3,638		3,102		2,216		7,101		6,370		4,866		5,065		4,486		3,207	
Panel B. Market Size / Book to Market Portfolios																		
	SMALL\ LOW						**SMALL\ MEDIUM**						**SMALL\ HIGH**					
Earnings per Dollar	4.6	9.9	5.0	12.9	12.0	19.4	7.8	10.8	8.5	13.1	13.0	21.2	8.9	14.7	10.0	18.8	15.5	24.0
Forecast Error AUF	-2.6	12.4	-4.7	14.5	-6.9	28.9	-2.5	11.6	-3.8	20.0	-6.3	25.0	-3.2	20.3	-4.6	22.7	-4.0	26.5
Forecast Error AAF1	-1.4	7.8	-3.0	11.9	-3.9	19.1	-1.3	9.1	-2.0	12.5	-3.8	21.0	-1.3	12.6	-2.0	17.9	-2.1	22.6
Forecast Error AAF2	-0.1	7.6	-1.8	11.9	-0.9	19.4	-0.2	8.8	-1.1	12.4	-1.2	20.9	0.1	12.2	-0.6	17.8	1.1	22.9
Forecast Error TSF	-0.3	8.4	-0.6	12.4	4.7	19.6	-0.6	9.2	-0.6	12.8	2.0	21.3	-1.2	13.1	-0.8	19.3	2.5	24.0
Observations	10,700		6,271		2,771		11,821		6,382		3,104		9,013		4,061		1,773	
	LARGE\ LOW						**LARGE\ MEDIUM**						**LARGE\ HIGH**					
Earnings per Dollar	5.6	3.7	6.5	4.5	10.7	8.4	8.4	5.4	9.0	6.6	12.6	12.0	9.6	9.4	10.5	11.6	13.3	16.4
Forecast Error AUF	-0.7	3.1	-1.5	4.9	-3.6	9.9	-1.1	4.8	-1.9	7.1	-3.3	13.2	-1.3	10.4	-2.0	12.3	-4.2	16.2
Forecast Error AAF1	-0.2	2.1	-0.7	3.5	-2.6	8.4	-0.4	3.8	-1.0	5.7	-2.2	11.6	-0.4	7.5	-1.1	10.2	-2.6	15.4
Forecast Error AAF2	-0.1	2.1	-0.5	3.5	-0.9	8.3	-0.1	3.9	-0.5	5.8	0.0	11.6	0.6	7.6	-0.1	10.4	0.4	16.0
Forecast Error TSF	-0.5	2.9	-0.3	4.1	2.5	8.5	-1.0	4.8	-1.4	6.6	0.5	12.2	-2.2	8.8	-2.6	11.7	-0.7	16.6
Observations	6,983		6,079		4,179		5,959		5,293		4,064		2,862		2,586		2,046	

Table 7. Dependent variable: Current year's forecast error of earnings per dollar

Start with CCIMC, get rid of the top and bottom 0.5% of fec0, resulting in 46,872 observations from 1982-2001. The coefficients estimates and t-values are calculated following the Fama-MacBeth approach.
DlowNoEst means that the total number of forecasts for the current year, next year, and long-run EPS growth rate for the firm is less than four.
Dwinner, Dloser, and Dother: winners and losers are stocks whose previous 12 months' returns fall in the top and bottom two deciles of the NYSE/AMEX past 12 month return deciles, excluding stocks with price less than $1.00 and NASDAQ stocks.
NASDAQ stocks and stocks with price less than $1.00 are "other" stocks. Value and Growth stocks are those whose book-to-market equity ratio falls in the top and bottom 2 deciles of NYSE book-to-market equity ratio deciles.
Big and Small stocks are those whose market capitalization falls in the top and bottom 2 deciles of NYSE market capitalization deciles.
High turnover and Low turnover are the top and bottom two deciles in terms of previous twelve months' average daily turnover, where NASDAQ stocks are ranked separately from NYSE/AMEX stocks; High accruals and Low accruals are the top and bottom two deciles in terms of accruals, where accruals are calculated according to Jiang et al. (2004).

Variable	Estimate	t value
Intercept	-0.0111	-3.79
DlowNoest	-0.0181	-9.55
Dwinner	0.0190	15.87
Dloser	-0.0220	-8.05
Dother	0.0054	3.05
Dvalue	-0.0051	-2.54
Dgrowth	0.0024	1.75
DBig	0.0044	4.84
Dsmall	-0.0190	-10.23
Dhighturnover	-0.0109	-8.04
DlowTurnover	0.0105	5.66
DhighAccruals	-0.0093	-9.82
DlowAccruals	-0.0153	-6.78

Table 8. Dependent variable is current year's long-run EPS growth rate forecast

Start with CCIMC, get rid of the top and bottom 0.5% of lrg (long-run EPS growth rate forecast) from the sample, Resulting in 37388 observations from 1982-2001.
The coefficients estimates and t-values are calculated following the Fama-MacBeth approach.
DlowNoEst means that the total number of forecasts for the current year, next year, and long-run EPS growth rate for the firm is less than four.
Dwinner, Dloser, and Dother: winners and losers are stocks whose previous 12 months' returns fall in the top and bottom two deciles of the NYSE/AMEX past 12 month return deciles, excluding stocks with price less than $1.00 and NASDAQ stocks.
NASDAQ stocks and stocks with price less than $1.00 are “other” stocks. Value and Growth stocks are those whose book-to-market equity ratio falls in the top and bottom 2 deciles of NYSE book-to-market equity ratio deciles.
Big and Small stocks are those whose market capitalization falls in the top and bottom 2 deciles of NYSE market capitalization deciles.
High turnover and Low turnover are the top and bottom two deciles in terms of previous twelve months' average daily turnover, where NASDAQ stocks are ranked separately from NYSE/AMEX stocks; High accruals and Low accruals are the top and bottom two deciles in terms of accruals, where accruals are calculated according to Jiang et al. (2004).

Variable	Estimate	t-value
Intercept	0.1124	38.28
DlowNoest	0.0026	1.56
Dwinner	0.0157	7.27
Dloser	0.0003	0.17
Dother	0.0332	8.89
Dvalue	-0.0267	-13.78
Dgrowth	0.0541	32.54
Dbig	-0.0176	-10.74
Dsmall	0.0236	18.73
Dhighturnover	0.0328	14.54
DlowTurnover	-0.0193	-5.23
DhighAccruals	0.0303	19.84
DlowAccruals	0.0151	5.06

Table 9. Analyst optimism, firm characteristics, and the average monthly return of next year.

Each year from 1982 to 2001, we perform the cross-sectional regression with the average monthly return of next year as the dependent variable, and analyst optimism measures and firm characteristic dummy variables as independent variables. We use Fama-MacBeth approach to calculate the coefficient estimates and t-tests. We use the Newy-West estimator to calculate the standard deviation of the (time series of) coefficients, allowing two leads and two lags. The total sample size is 44,445 observations. Each observation is a firm year. The values of the independent variables are their prevailing values at nine months before the end of the fiscal year. DhighLrg and DlowLrg denote the top and bottom two deciles of current lrg (long-run EPS growth rate forecast) rankings. DhighFec0 and DlowFec0 denote the top and bottom two deciles of previous year's forecast error in earnings per dollar (after taking out special items). DlowNoEst means that the total number of forecasts for the current year, next year, and long-run EPS growth rate for the firm is less than four. Dwinner, Dloser, and Dother: winners and losers are stocks whose previous 12 months' returns fall in the top and bottom two deciles of the NYSE/AMEX past 12 month return deciles, excluding stocks with price less than $1.00 and NASDAQ stocks. NASDAQ stocks and stocks with price less than $1.00 are "other" stocks. Value and Growth stocks are those whose book-to-market equity ratio falls in the top and bottom 2 deciles of NYSE book-to-market equity ratio deciles. Big and Small stocks are those whose market capitalization falls in the top and bottom 2 deciles of NYSE market capitalization deciles. High turnover and Low turnover are the top and bottom two deciles in terms of previous twelve months' average daily turnover, where NASDAQ stocks are ranked separately from NYSE/AMEX stocks; High accruals and Low accruals are the top and bottom two deciles in terms of accruals, where accruals are calculated according to Jiang et al. (2004). T-values are in parenthesis. * and ** denote significant at the 10% and 5% confidence level.

Independent variables	Equation 1	Equation 2	Equation 3	Equation 4
Intercept	0.0152** (6.63)	0.0148** (6.93)	0.0132**(5.62)	0.0132** (5.40)
DhighLrg	-0.0039* (-1.83)			-0.0008 (-0.60)
DlowLrg	-0.0006 (-0.38)			-0.0003 (-0.35)
DhighFec0		0.0001 (0.12)		0.0006 (0.71)
DlowFec0		-0.0002 (-0.09)		-0.0003 (0.18)
DlowNoEst			0.0000 (0.00)	-0.0001 (-0.07)
Dwinner			0.0022* (1.92)	0.0022** (2.16)
Dloser			-0.0017 (-0.79)	-0.0017 (-0.86)
Dother			0.0037**(2.75)	0.0037** (2.86)
Dvalue			0.0019**(3.42)	0.0019** (3.24)
Dgrowth			-0.0023 (-1.58)	-0.0022 (-1.51)
Dbig			0.0009 (0.64)	0.0009 (0.60)
Dsmall			0.0015 (0.99)	0.0015 (1.05)
DhighTurnover			-0.0044**(-3.92)	-0.0043** (-4.39)
DlowTurnover			-0.0012 (-0.62)	-0.0011 (-0.61)
DhighAccruals			-0.0041**(-3.88)	-0.0041** (-3.85)
DlowAccruals			0.0026 (1.47)	0.0027 (1.63)

Table 10. Analyst optimism, firm characteristics, and the total return of next year.

Each year from 1982 to 2001, we perform the cross-sectional regression with the total return of next year as the dependent variable, and analyst optimism measures and firm characteristic dummy variables as independent variables. We use Fama-MacBeth approach to calculate the coefficient estimates and t-tests. We use the Newy-West estimator to calculate the standard deviation of the (time series of) coefficients, allowing two leads and two lags. The total sample size is 44,445 observations. Each observation is a firm year. The values of the independent variables are their prevailing values at nine months before the end of the fiscal year. DhighLrg and DlowLrg denote the top and bottom two deciles of current lrg (long-run EPS growth rate forecast) rankings. DhighFec0 and DlowFec0 denote the top and bottom two deciles of previous year's forecast error in earnings per dollar (after taking out special items). Dwinner, Dloser, and Dother: winners and losers are stocks whose previous 12 months' returns fall in the top and bottom two deciles of the NYSE/AMEX past 12 month return deciles, excluding stocks with price less than $1.00 and NASDAQ stocks. NASDAQ stocks and stocks with price less than $1.00 are "other" stocks. Value and Growth stocks are those whose book-to-market equity ratio falls in the top and bottom 2 deciles of NYSE book-to-market equity ratio deciles. Big and Small stocks are those whose market capitalization falls in the top and bottom 2 deciles of NYSE market capitalization deciles. High turnover and Low turnover are the top and bottom two deciles in terms of previous twelve months' average daily turnover, where NASDAQ stocks are ranked separately from NYSE/AMEX stocks; High accruals and Low accruals are the top and bottom two deciles in terms of accruals, where accruals are calculated according to Jiang et al. (2004). T-values are in parenthesis. * and ** denote significant at the 10% and 5% confidence level.

Independent variables	Equation 1	Equation 2	Equation 3	Equation 4
Intercept	0.1861** (5.27)	0.1795** (5.47)	0.1731**(5.37)	0.1725** (5.08)
DhighLrg	-0.0493 (-1.60)			-0.0006 (-0.03)
DlowLrg	-0.0021 (-0.09)			-0.0077 (-0.73)
DhighFec0		0.0094 (0.48)		0.0112 (0.93)
DlowFec0		0.0125 (0.37)		0.0123 (0.45)
DlowNoEst			-0.0106 (-0.62)	-0.0104 (-0.55)
Dwinner			0.0270 (1.68)	0.0275* (1.96)
Dloser			-0.0279 (-1.18)	-0.0287 (-1.45)
Dother			0.0481**(2.19)	0.0473** (2.26)
Dvalue			0.0227**(2.07)	0.0221* (1.93)
Dgrowth			-0.0517* (-1.91)	-0.0506* (-1.90)
Dbig			0.0065 (0.34)	0.0078 (0.41)
Dsmall			0.0203 (0.91)	0.0193 (0.92)
DhighTurnover			-0.0611**(-3.60)	-0.0632** (-4.28)
DlowTurnover			-0.0094 (-0.28)	-0.0070 (-0.22)
DhighAccruals			-0.0555**(-2.71)	-0.0568** (-2.68)
DlowAccruals			0.0283 (1.02)	0.0270 (1.04)

Figure 1 – Special Items and the Forecast Error

Figure 1.1 presents the relation between the forecast error FEX (actual earnings per dollar before extraordinary items (EX) – earnings forecast per dollar) and the special items per dollar (sitpd). Figure 1.2 presents the relation between the forecast error FE (actual earnings per dollar before extraordinary *and special items* (E) – earnings forecast per dollar) and the special items per dollar (sitpd). To obtain values per dollar we divide values per share by its price 12 months before. There are 10,739 observations in each figure. From our sample (26,943 observations), we delete 16,185 for which special items were either zero or not available. We further delete 19 outliers, 15 due to the fact that their sitpd was less than –1 and 4 because this value was larger than 1. The deletion is made for expository motives only and only for these two figures. All results in the paper are provided including the outliers. See text for additional details.

Figure 1.1 – Special Items and the Forecast Error FEX

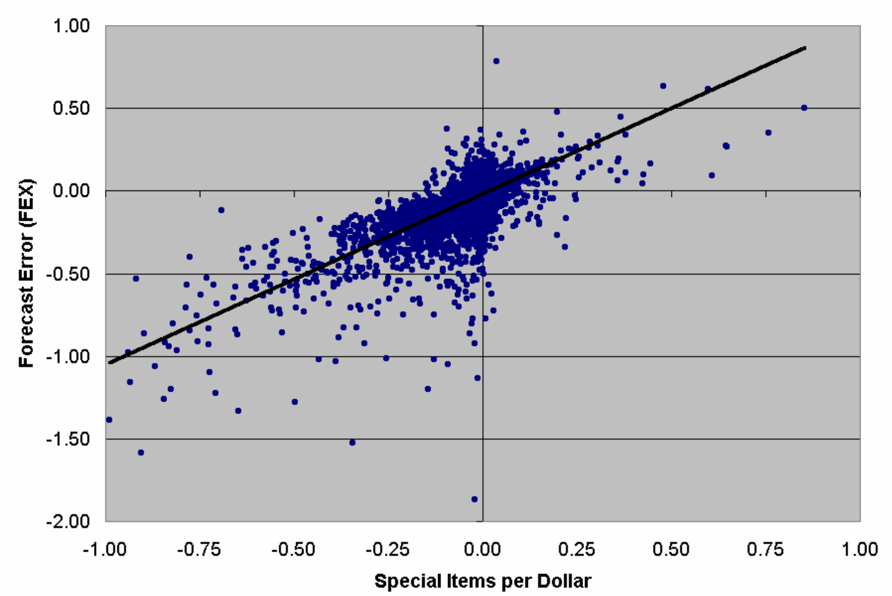

Figure 1.2 – Special Items and the Forecast Error FE