On the Relation between Market and Analyst Forecast Inefficiencies

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Abstract

We examine the relation between market and analyst forecast inefficiencies. Using a common set of public information variables, we find 1) both abnormal stock returns and analyst earnings forecast errors are predictable; 2) while future analyst forecast errors are positively correlated with the predictable component of abnormal returns, future abnormal returns are not significantly correlated with the predictable component of forecast errors; 3) in contemporaneous regressions of stock returns on analyst forecast errors, removing the predictable component of analyst forecast errors results in higher coefficient estimates and R^2 values; but in the reverse regressions, removing the predictable component of stock returns does not generate a similar effect. Our results suggest an asymmetric relation between market and analyst forecast inefficiencies, and that analyst forecasts embed more inefficiency than market pricing. This conclusion has important implications for capital markets research and portfolio management.

1. Introduction

A common issue in market anomaly studies is the prospect that omitted risk factors, rather than market inefficiency, might explain findings of predictable stock returns based on public information. One approach for addressing this issue is to examine whether the predictable returns are associated with the predictable analyst earnings forecast errors, with a positive finding consistent with market inefficiency. Evidence of such an association has been found for well-known market anomalies, such as the post-earnings-announcement drift (Bernard and Thomas [1989], Mendenhall [1991]), the accrual anomaly (Sloan [1996], Bradshaw, Richardson and Sloan [2001]), and the price momentum (Jagadeesh and Titman [1993], Abarbanell [1991]). However, a question that remains is whether the same phenomena are driving both market and analyst forecast inefficiencies. Research to date is not discriminating on this issue.

In this study, we assess the relation between market and analyst forecast inefficiencies using a prediction test and an association test. In the prediction test, we forecast future abnormal returns and analyst forecast errors based on a common set of public information inclusive of ten variables identified by prior research as having predictive content.[1] Consistent with prior research, we find significant predictability in both abnormal stock returns and analyst forecast errors. More notably, we find the predictable forecast errors are not associated with future abnormal returns and, yet, the

[1] In particular, we include three "under-reaction" variables (earnings surprise, stock returns and analyst earnings forecast revisions) and seven "over-reaction" variables (book to price ratio, forward earnings to price ratio, analyst long term growth forecast, sales growth, investments in property, plant and equipment, investments in other long-lived assets, and the accrual component of earnings). We discuss these variables in more detail in section 2.

predictable component of abnormal returns is positively associated with future forecast errors.

These findings suggest that market and analyst inefficiencies are not isomorphic. Rather, we take them to imply the hypothesis that beyond whatever inefficiencies the market and analysts may have in common, analyst forecasts exhibit more inefficiencies absent in market pricing. The unique inefficiencies in analyst forecasts can act as measurement noise to bias coefficient estimates toward zero in the mapping from future abnormal returns to the predictable component of forecast errors, but have no effect on the converse relation between future forecast errors and the predictable component of abnormal returns.

In addition to the prediction test, our hypothesis suggests an association test: if analysts' inefficiency measures market inefficiency with noise, then naturally analysts' earnings forecasts and market earnings expectations may also differ by this noise. Accordingly, in contemporaneous regressions of market returns on earnings surprises, when analyst forecasts are used as a proxy for market earnings expectations, both coefficient estimates and goodness-of-fit measures may be biased downwards, and the bias can be alleviated by removing the noise term. Our empirical findings are consistent with this conjecture. Comparing unadjusted regression results with those in which we adjust analysts' forecasts by removing the predictable component of forecast errors, we find significant increase in regression coefficient estimates and R^2 values as a result of the adjustment. Moreover, reversing the regressions such that unadjusted analysts' forecast errors are regressed on contemporaneous abnormal returns, we find that the adjustment to remove the predictable component of abnormal returns does not generate a

similar effect. Therefore, our hypothesis that analysts' forecasts exhibit more inefficiency than market pricing is supported by results from both the prediction and the association tests.

Several economic arguments can be made to explain such an asymmetric relation. First, since sell-side analysts are intermediaries with no direct monetary stake at risk from their forecasts, they are likely to have less incentive than investors who have such a stake to "get the numbers right." Second, even when judgment errors are detected, analysts may revise their earnings forecasts less rapidly than the market due to the same incentive problem. Third, the inherent conflicts of interests built in sell-side analysts' business model – investment banking versus primary research, appeasement of management versus objective analysis (e.g., Francis and Philbrick [1993], Alford and Berger [1997]) – suggest that analysts may have incentives to intentionally distort their earnings forecasts.[2]

Our empirical results confirm that analyst forecasts embed large inefficiencies. At the annual horizon, we find that the optimistic bias in analyst forecasts can be reduced in each year examined, by an average of over forty percent judged by the averages and over seventy percent judged by the medians. The dispersion of forecast errors can be reduced in eleven out of twelve years examined, by an average of about thirty percent in mean squared errors or ten percent in mean absolute errors. Moreover, we find that the inefficiencies are mostly embedded in forecasts that are predicted to be too optimistic, with the underlying firms smaller and more thinly covered by analysts.

[2] These strong arguments in favor of more relative inefficiency on the part of analysts are mitigated by the possibility that correlated trading by noise traders susceptible for psychological biases could drive prices away from fundamentals, and that the forces of arbitrage are limited (Shleifer and Vishny [1997]).

Our finding that analysts exhibit more inefficiency than the market has important implications for both academic research and practice. For academic research, our results lend support to the growing practice of using predictability in analyst forecast errors to assess the likelihood of predictable abnormal returns being driven by market inefficiency (e.g., Bradshaw, Richardson and Sloan [2006]). For practitioners, especially those who work in the field of money management, our results provide guidance on how one could design profitable trading strategies. To the extent that there are inefficiencies in market prices and they are related to errors in expectations about future firm fundamentals, one can take one of the following two approaches to exploit such inefficiencies: the first approach is to build a trading strategy directly based on predicted future returns and later verify the likelihood of risk versus inefficiency using analyst forecast errors; and the second approach is to predict analyst forecast errors first and then build a trading strategy based on the predictable component of forecast errors. Though on the surface the two approaches appear equivalent, our results suggest that sequence matters and the former approach is more likely to be successful than the latter, because of the asymmetric relation between market and analyst forecast inefficiencies.

The rest of the paper is organized as follows: section 2 discusses research design issues; section 3 describes our sample; section 4 presents empirical results; and section 5 concludes the paper.

2. Research design issues

Following Ou and Penman [1989] and Lev and Thiagarajan [1993], we consider a comprehensive though not exhaustive list of publicly available information variables that

are likely to be associated with market and analyst inefficiencies. In doing so, we maximize the generality of our results. The tradeoff is that each prediction variable receives less attention than studies that look at a small set of prediction variables. Specifically, we consider three "under-reaction" variables (price momentum, earnings surprise, and analysts' earnings revisions) and seven "overreaction" variables (book to price ratio, forward earnings to price ratio, analyst long term growth forecast, sales growth, investments in property, plant and equipment, investments in other long-lived assets, and the accrual component of earnings), which are identified by prior research as having predictive content over future stock returns or analyst forecast errors.

Prior research that documents analysts' under-reaction to recent information includes Mendenhall [1991] (under-reaction to quarterly earnings announcements), Abarbanell [1991] (under-reaction to past price changes) and Gleason and Lee [2003] (under-reaction to past earnings forecast revisions). Similar sluggish reactions have been found for market returns with respect to the three under-reaction variables (Bernard and Thomas [1989], Jagadesh and Titman [1993] and Stickel [1991]).

Among the seven over-reaction variables, the accrual component of earnings is first identified by Sloan [1996], and subsequently confirmed by a number of follow-up studies as having negative predictive power over future returns. Sloan concludes that the return prediction power of accruals is due to the market's failure in understanding the differential persistence of accruals versus cash flows. Following similar lines, Bradshaw et al [2001] find that analysts and auditors also make a similar mistake.

Book to price ratio, forward earnings to price ratio, past sales growth and analysts' long term earnings forecasts have been studied by Frankel and Lee [1998], who

show a negative correlation between these variables and future analyst forecast errors.[3] Past sales growth has also been studied by La Porta [1996] who documents that the stock market seems to naïvely extrapolate past growth in sales, and that past sales growth is negatively correlated with future returns. Analysts' long-term earnings growth forecasts have been considered by Dechow, Hutton and Sloan [2000], who find that analysts are overly optimistic in making long term growth forecasts for firms issuing stocks, and that the levels of these forecasts are negatively correlated with future returns.[4]

The remaining over-reaction variables are motivated by a recent study by Titman, Wei and Xie [2004], who document a negative relationship between capital expenditures and subsequent abnormal returns. They argue that firms with high profitability in prior periods generate more free cash flows, which result in reduced future profitability and negative abnormal returns because of increased investments in negative net present value capital expenditures.

In order to enhance the robustness of analysis, we focus on out-of-sample predictions rather than in-sample fit. Specifically, in each year, one month after the release of annual earnings,[5] we use the data from the past five years to estimate the coefficients of a predictive regression model; we then pick the prediction variables that are statistically significant and apply the estimated coefficients to the current values of prediction variables to forecast the earnings forecast errors and abnormal returns for the upcoming year. To gauge the efficacy of the model in predicting abnormal returns, we

[3] Forward earnings to price ratio is a proxy for the V/P ratio in Frankel and Lee [1998].
[4] We note that analysts cannot over-react or under-react to their own forecasts. Long term earnings growth forecasts are interpreted here as a proxy for the level of analysts' inefficiency in their reaction to some latent information variables. The "over-reaction" classification simply reflects the fact that the level of long term growth forecasts are negatively correlated with future returns.
[5] We also tried forecasts at two or three months after earnings announcements. The results are very similar.

tabulate the realized long-short hedge returns for portfolios formed based on predicted abnormal returns. For analyst earnings forecasts, we modify analysts' earnings forecasts using the predicted errors and compare the accuracy and precision of the resulting adjusted forecasts with those of the unadjusted forecasts.

Our model estimation procedures include both the traditional OLS and an alternative Least Absolute Deviation (LAD) procedure. Similar to OLS, LAD assumes a linear relation between the dependent and the independent variables:

$$y_i = \beta x_i + \varepsilon_i ,$$

where y_i is the dependent variable, x_i is a vector of independent variables, β is a vector of coefficients, and ε_i is the residual. Instead of minimizing the sum of squared errors as in OLS, the LAD method minimizes the sum of absolute deviation to estimate the beta coefficients:

$$\min_{\beta} \sum_i |\varepsilon_i| .$$

The resulting LAD estimate can be interpreted as measuring the median of *y* conditional on *x*, i.e.,

$$MEDIAN\left(y_i \mid x_i\right) = \beta x_i .$$

Because LAD estimation is less influenced by outliers than OLS, it is often classified as a robust estimator (Kennedy [2003]).[6] In addition to the desirable robustness property, the LAD estimator also helps to alleviate concerns raised in recent research such as Gu and Wu [2003] and Basu and Markov [2004] that analysts' true objective may be the minimization of mean absolute errors. Although we conduct tests using both OLS and

[6] To implement LAD estimation, we use the LAV routine in the SAS/IML, which applies the algorithms in Madsen and Nielsen [1993] to estimate coefficients and McKean and Schrader [1987] to estimate the variance-covariance matrix. We thank Stan Markov for pointing out the source of this routine.

LAD, to save space, we only report results generated under LAD. We find that while the in-sample results under OLS and LAD are similar, LAD generates stronger prediction results out of sample due to its robustness property.[7]

3. Data and sample selection

We obtain earnings forecasts and actual earnings from *I/B/E/S*. All per share data in *I/B/E/S* are adjusted for stock splits and stock dividends using the *I/B/E/S* adjustment factors. We obtain stock price and return data from *CRSP* monthly tape, and financial statement data from the industrial, full coverage and research tapes of *COMPUSTAT*. We include in our sample every observation for which we can calculate the variables needed in the analysis (Table 1). Some of the data requirements, such as the requirement of five years of sales data, availability of earnings announcement dates, two-year-ahead earnings forecasts and long-term EPS growth rate forecasts, significantly reduce our sample size. Our final sample includes 15,409 firm-year observations and spans the time period from 1984 to 2000.

Table 1 reports the summary statistics of the variables used in this study, Panel A reports the marginal distributions, Panel B reports the correlation matrix. In each year, one month after announcement of annual earnings, we measure the following list of variables:

Error: Consensus analyst forecast error, i.e., actual *I/B/E/S* earnings for the next fiscal year minus the median analyst earnings forecast, deflated by stock price. Both the earnings estimates and stock prices are measured one month after the most recent annual earnings release.

[7] OLS results are available upon request.

Fret: Size-adjusted future abnormal stock returns, accumulated in the 13 months after the measurement of *Error*.[8]

MV: Market value, price per share times the number of shares outstanding from *CRSP*, measured at the same time as *Error*.

Cover: Analyst coverage, defined as the number of all analysts who issued earnings forecasts for the firm for the upcoming year.

Acc: Accounting accruals in the most recent annual earnings, measured as the change in non-cash current assets minus depreciation and the change in current liabilities, excluding the current portion of long-term debts and tax payables. It is standardized by the average total assets in the past two years.

B/P: Book-to-market ratio, which is book value per share from the most recent balance sheet over the stock price from *CRSP*, the stock price is measure at the same time as *Error*.

E/P: Forward Earnings/price ratio, i.e., analysts' earnings forecast for the two-year-ahead annual earnings over stock price from *I/B/E/S*, both measured at the same time as *Error*.

Ltg: Analyst long-term EPS growth rate forecast, measured at the same time as *Error*.

Ltsg: Annualized long-term sales growth rate in the past five years.

ΔPPE: Change of Property, Plant and Equipment from the previous year, standardized by the average total asset in the last two years.

[8] Return window of thirteen months is chosen to capture the realization of earnings in the next fiscal year. The results are essentially the same when we use a twelve-month window for returns.

ΔOLA: Change of other long-term assets from the previous year, standardized by the average total asset in the last two years.

UE: The earnings surprise for the most recent fiscal quarter, standardized by stock price from *I/B/E/S*.

Ret: Raw stock return in the past 12 months before the measurement of *Error*.

Rev: Revision of the consensus analysts' forecast during the 3 months before the measurement of *Error*, standardized by stock price from *I/B/E/S*.

(Insert Table 1 about here)

Inspecting the first row of Panel A, we find that analysts are too optimistic judging from the mean forecast error (-2.4% of stock price). However, the median forecast is only marginally negative (-0.3% of stock price), suggesting analysts are not too optimistic if they intend to forecast the median. Consistent with prior literature, we also find that analyst forecast errors are left skewed. The first percentile cutoff point has a value of -0.305, in contrast with 0.072 for the 99th percentile; the 25th percentile cutoff value is -0.021, in contrast with 0.003 for the 75th percentile. The fact that analysts make more mistakes in the left tail (optimism) suggests that forecasting improvement, if there is any, may also have more room in this area. The market capitalizations of our sample firms are on average larger than the average firm size on NYSE, AMEX and NASDAQ, reflecting the fact that analysts tend to follow larger companies. The firms' mean analyst coverage is 19.6 and median coverage is 16, with less than half of the firms covered by less than 9 or more than 30 analysts.

Consistent with Sloan [1996] and Bradshaw et al. [2001], accounting accruals on average are income reducing, with mean (median) of -3.5% (-3.9%) of total assets. The

mean and median of *B/P* ratios are in the neighborhood of 0.5. The average forward *E/P* ratio of our sample is 0.08, suggesting an average *P/E* ratio of 12.5. This divergence from average trailing earnings based *P/E* ratio is expected because the two-year-out earnings forecasts build in expected earnings growth for the next two years (Claus and Thomas [2001]). The median growth rates based on analyst forecasts agree with historical experience in median revenue growth, with values around 13% to 14%, though *Ltg* forecasts have a much tighter distribution than the realized *Ltsg*. In addition to the high variation, *Ltsg* is highly skewed to the right, with some firms experiencing very fast growth. Consistent with the notion that the average firm in our sample is growing, we find the average investment in Property, Plant and Equipment as well as Other Long-lived Assets is about 3% of Total Assets.

In Panel B, Spearman rank correlations are reported above the main diagonal and Pearson correlations are reported below the diagonal. Although in most cases the two correlation measures are consistent, in a few cases they have different signs due to non-linearity or outliers. We primarily use Spearman rank correlations to interpret the results. The correlation matrix is largely consistent with findings reported in prior literature. First, forecast errors (*Error*) are highly correlated with their contemporaneous abnormal returns (*Fret*), confirming the general earnings/return relationship. Second, the forecast errors are negatively correlated with the over-reaction variables (*Acc*, *B/P*, *E/P*, *Ltg*, *Ltsg*, *ΔPPE*, *ΔOLA*) and positively correlated with the under-reaction variables (*UE*, *Ret*, *Rev*). The P-values for the Spearman correlation estimates are significant at conventional levels for all variables except *ΔOLA*. While most of these correlations have been documented in prior literature, our finding that analysts over-react to corporate investments in Property, Plant

and Equipment is new, and complements Titman et al's [2004] finding that the market over-reacts to such investments. Third, future abnormal returns (*Fret*) show similar correlation patterns with the over-reaction and the under-reaction variables, though the strength of correlations and significance levels are in general much lower,[9] suggesting that market prices are more efficient than analyst forecasts in reflecting available information. Fourth, the correlations among the forecasting variables are low to modest. Maximum correlations are found between *Ltsg* and *Ltg* (0.588), and *Ret* and *Rev* (0.401). This implies that the information contents in these variables are largely orthogonal, hence forecasting may be improved by combining these variables in a single model.

4. Results

4.1 Forecasting analyst forecast errors

Table 2 presents the in-sample pooled regression results estimated using the LAD procedure. We separate the prediction variables into three groups: accounting accruals (*Acc*), over-reaction variables (*B/P*, *E/P*, *Ltg, Ltsg*, *ΔPPE*, *ΔOLA*), and under-reaction variables (*UE*, *Ret*, *Rev*). *Acc* is separated from other over-reaction variables because prior literature analyzed accruals in isolation (e.g., Sloan [1996] and Bradshaw et al [2001]). Because a R^2 type goodness-of-fit measure is not available for the LAD procedure, we only report the coefficient estimates and associated t-values.

(Insert Table 2 about here)

The first row of Panel A presents the simple regression results based on accounting accruals. Consistent with Bradshaw et al [2001], we find accounting accruals

[9] The P-values for the Spearman correlation estimates are 0.01% for *Acc*, *Ltg, ΔPPE*, *ΔOLA*, *UE*, *Ret* and *Rev*, 24.3% for *B/P,* 26.5% for *E/P,* 2.0% for *Ltsg*.

are negatively correlated with future analyst forecast errors, with a coefficient estimate of -0.016 and t-value of -9.59. The results on the over-reaction variables are broadly consistent with results reported in prior literature. The negative coefficients suggest that analysts over-react to information contained in these variables and the over-reaction is later verified by realized earnings. Among the over-reaction variables, *Ltsg* and *ΔOLA* are not statistically significant from zero, and *Ltsg* even has the wrong sign, which is likely due to its high correlation with *Ltg.* The results on the under-reaction variables are also consistent with prior research. The coefficient estimates on *UE*, *Ret* and *Rev* are all highly significant with positive values. Combining all the prediction variables, in the last row, we show that the results obtained in the separate regressions are well preserved.

Table 2 suggests that analyst inefficiency is a robust phenomenon even under LAD. This is in contrast with a recent paper by Basu and Markov [2004] who show that LAD mitigates the inefficiency finding demonstrated in the prior literature under OLS. In analysis available but not reported here, we show that the differences arise because 1) we examine a larger set of prediction variables, and 2) we measure both earnings forecasts and forecast errors at one-year horizon in Table 2, while in Basu and Markov [2004] annual earnings expectations are measured at one month before annual earnings announcements, effectively making their annual earnings surprises equivalent to the earnings surprises of the last fiscal quarter, since the first three quarters of earnings are already known at the measurement date.

The in-sample results reported in Table 2 potentially overstate the significance because, for an analyst who has to forecast earnings in real time, she can only observe what happened in the past, but not the whole data series as assumed in Table 2. This

potential bias can be alleviated by conducting out-of–sample analysis, which may produce result different from that produced in sample. For example, in a recent paper, Goyal and Welch [2003] found that dividend to price ratio fails to predict equity premium out of sample although it shows good in-sample fit. In out-of-sample prediction test, each year we first estimate the full model using the past five years of data, then apply the estimated coefficients (insignificant coefficient estimates are set to zero) to the current values of the independent variables to predict the forecast errors. We then use predicted forecast error as an adjustment to modify the *I/B/E/S* consensus forecast and evaluate the success of the prediction by examining the precision and accuracy of the modified forecast in comparison with the original *I/B/E/S* consensus. Out-of-sample prediction starts in 1989, since the first five years' (1984-1988) data are used for model estimation. Results are presented in Table 3.

(Insert Table 3 about here)

Panel A reports the year-by-year distribution of analyst forecast errors. In every sample year, the mean and median forecast errors are negative, suggesting analyst optimism is a robust phenomenon. The skewness of the distributions is also evident because the means are more negative than the medians. The average mean is -0.019 and the average median is -0.0037. To capture the dispersion of the distribution, we report three measures: standard deviation, mean squared error (*MSE*) and mean absolute error (*MAD*).

Panel B presents the distribution of analyst forecast errors after the forecasts are adjusted by out-of-sample prediction. In each year, both bias and dispersion of analyst forecast errors are substantially reduced. The mean (median) of the distribution is

reduced from -1.88% (-0.37%) of stock price to -1.04% (-0.1%) of stock price, or a 45% (73%) drop in percentage terms. The dispersion measures also decrease across the board. In 11 of the 12 sample years, standard deviation, *MSE* and *MAD* decrease. On average, standard deviation of forecast errors decreases by 14.5%, *MSE* decreases by 34.6%, and *MAD* decreases by 9.1%.[10]

Following Fama and MacBeth [1973], we test the statistical significance of the prediction result by treating each year's reductions in *MSE* and *MAD* as independent realizations of two random variables. We then test whether the times series means are statistically significantly different from zero. The t-statistics are highly significant, 4.29 for *MSE* and 4.68 for *MAD.*

4.2 Sources of improvement

In this section we investigate the sources of improvement documented in Table 3. Motivated by the results of Easterwood and Nutt [1999] who document asymmetric inefficiency in analyst forecasts, we sort stocks into decile portfolios based on the (*ex ante*) predicted value of forecasted errors, and examine whether the forecast improvement happens asymmetrically across portfolios. Results are reported in panel A of Table 4. From portfolio 1 to portfolio 10, the predicted earnings forecast errors go from the most negative to the most positive. For each portfolio, we report the mean and median of actual forecast errors, the mean and median of forecast errors based on adjusted forecasts, the amount of improvement in *MAD* after the adjustment, and the frequency at which the adjusted forecasts are more accurate than the unadjusted forecasts.

[10] The smaller reduction in *MAD* than *MSE* could be partially due to the fact that *MSE* is a convex function on forecast errors and *MAD* is a linear function. It is also consistent with the hypothesis that analysts' true loss function is closer to minimizing the sum of absolute errors.

(Insert Table 4 about here)

It is clear that the out-of-sample predictions are generally in the correct directions as implied by the monotonicity of actual means and medians from portfolio 1 to 10. It is also clear that our model offers only a partial adjustment because the monotonicity is preserved for the adjusted means and medians. For seven out of the ten portfolios, the adjusted forecasts are more precise than the original forecasts. What is striking is that most of the improvement happens in portfolios where analyst forecasts are predicted to be too optimistic. In portfolios where our model predicts pessimism on the part of analysts, the adjustments in fact make the forecasts less precise. Consistent with Easterwood and Nutt [1999], our results imply that analysts are efficient in impounding good news in their forecasts, but are inefficient in impounding bad news.

In Panel B we examine the characteristics of firms in each portfolio to see how the portfolios that offer improvement differ from other portfolios. As expected, we find that the improved portfolios are in general those that receive the least attention in the stock market: they are smaller in size and more thinly covered by analysts. Inspecting the values of the prediction variables, we find variables such as *B/P* ratio, *E/P* ratio, *ΔPPE*, *UE*, *Ret*, and *Rev* are monotonic across the portfolios, suggesting that overall these variables are the primary drivers for the portfolio separation. Of course, in any particular year, the weights that are assigned to these variables for prediction can vary.

4.3 Robustness issues

The large inefficiency we document about analysts' forecasts may seem surprising to some. In order to ensure that our results are robust, we conduct several additional tests.

First, there might be concern that our results are due to the particular measurement of analysts' forecasts we adopt. We address this issue in two ways. First, we replace median consensus forecasts with mean consensus forecasts and find the results are essentially the same. Second, we address the issue that the consensus may contain stale forecasts by replacing the consensus forecasts with the latest individual forecasts issued within one month after earnings announcements and repeating the analysis. The results are qualitatively similar though smaller in magnitude.

Second, since most of the improvement in forecast accuracy comes from forecasts that are predicted to be too optimistic, a question naturally arises whether an intercept adjustment by itself is driving the whole result. We find this is not the case. If we only adjust for analysts' global optimism with an intercept, the improvement in analysts' forecast accuracy, measured by *MSE* and *MAD,* is negligible.

Third, a concern about out-of-sample prediction test is that there is no theory that can guide us on how to most efficiently use past data for estimation. On one hand, one could argue that one should use all available data because more data generates more efficient estimates. On the other hand, to the extent that there could be regime shifts during the sampling period, using more recent data may generate coefficients more fitting to the current regime. Our choice of using five year rolling regressions is a compromise between these two concerns. To address the former concern, we also extend the data to ten years and all available data. The results are essentially the same.

4.4 Predicting size-adjusted abnormal returns

Having established that analyst forecast errors are predictable out of sample, we now turn our attention to the prediction of future size-adjusted abnormal returns. Panel A of Table 5 presents the pooled coefficient estimates of our prediction model, where the prediction variables are the same as in prior tables and the dependent variable is now future size-adjusted abnormal returns, measured over 13 months starting one month after the release of earnings for the last fiscal year.[11] Consistent with prior research, all over-reaction (under-reaction) variables have negative (positive) signs. All prediction variables except *B/P, Ltsg,* and *Rev* are statistically significant.

(Insert Table 5 about here.)

To predict abnormal returns out of sample, in each year, we follow the same procedure as in prior tables and conduct rolling LAD regressions using the preceding five years of data to estimate the model parameters, and then form predictions of next thirteen month's abnormal returns using the most recent realizations of the prediction variables. We then divide the sample into five quintile portfolios based on the predicted abnormal returns. Panel B tabulates the realized equally-weighted size-adjusted abnormal returns for each portfolio as well as a hedge return that is long in quintile 5 and short in the quintile 1. The results are consistent with the notion that the stock market does not impound public information efficiently. As shown in the last row of Panel B, we observe that the mean abnormal returns increase monotonically from portfolio 1 to portfolio 5. In

[11] We choose a thirteen month window to ensure that the return period covers the announcement of next annual earnings.

addition, in ten out of twelve years examined, we observe positive returns for the hedge portfolio, with a global mean of 9% for the thirteen month period.

Given that the same set of prediction variables can be used to forecast analyst earnings forecast errors and future abnormal returns out of sample, one can easily conjecture that the two results might be related. We note, however, it is an empirical question whether a positive relation between the two exists because the regression loadings on the prediction variables can differ substantially. For example, while both book-to-price ratio and analyst earnings forecast revisions are statistically significant in predicting analyst forecast errors, they are insignificant in the prediction of future abnormal returns, suggesting different mechanisms are at work for the observed predictability in returns and earnings forecast errors.

4.5 *The relation between market and analyst inefficiencies*

To analyze the relation between market and analyst inefficiencies, it is useful to divide the inefficiencies into three components: a common component shared by both the market and analysts, an idiosyncratic component uniquely possessed by analysts, and an idiosyncratic component uniquely possessed by the market. The relation has four possible scenarios: The first one is that both idiosyncratic components are relatively unimportant compared with the common component, and thus the predictabilities in abnormal returns and in analyst forecast errors are essentially equivalent; the second scenario is that both idiosyncratic components dominate the common component such that the two inefficiencies are unrelated in data; the third and fourth scenarios are immediate cases where one idiosyncratic component is important while the other is not,

relative to the common component. On approach to distinguish the four scenarios is to examine whether future forecast errors (abnormal returns) are positively associated with the predictable component of abnormal returns (forecast errors): the first scenario implies positive results in both directions; the second scenario implies negative results in both directions; the third and fourth scenarios imply asymmetric results. If the idiosyncratic component of the market's (analysts') inefficiency is relatively small (large), then, while future forecast errors will be positively correlated with the predictable component of abnormal returns, future abnormal returns may not be positively correlated with the predictable component of forecast errors. The opposite will be true if the idiosyncratic component for market (analyst) inefficiency is relatively large (small). Table 6 contains the results.

(Insert Table 6 about here)

In Panel A, we first form quintile portfolios based on predicted abnormal returns, and then calculate mean forecast errors for each portfolio based on one year out and two year out earnings forecasts. The results indicate that forecasts errors are positively correlated with portfolio ranks for both one-year-out and two-year-out forecasts. For the hedge portfolio that is long in portfolio 5 and short in portfolio 1, the differences in forecast errors are 2.7% of the stock price for one-year-out forecasts (t-value 3.792) and 3.8% of stock price for two-year-out forecasts (t-value 5.02). These results suggest that analysts make some common errors as the market and the idiosyncratic component of market inefficiency is not large enough to mask the detection of analyst inefficiency on the basis of predictable abnormal returns. This result is consistent with prior findings by Abarbanell and Bernard [1992] and Bradshaw et al [2001].

In panel B, we reverse the analysis and sort firms into quintile portfolios based on predicted one-year-out EPS forecast errors, and then examine whether the future abnormal returns are positively sloped in the portfolio ranks. Future abnormal returns are measured over the next four months and thirteen months to allow for both short-term and long-term price adjustments by the market. We find little evidence of a positive correlation between portfolio ranks and abnormal returns. With the exception of the two portfolios with the largest predicted forecasts errors, portfolios exhibit no pattern in the magnitude of abnormal returns. Returns to the hedged portfolio going long in portfolio 5 and short in portfolio 1 are not statistically significant for any return horizon.[12] This result suggests that the idiosyncratic component in analyst inefficiency is large relative to the common component, and since this idiosyncratic component has nothing to do with market inefficiency, it becomes a source of noise that biases the test toward the null.

In sum, our results are consistent with but one of the four possible scenarios, that the relation between market and analyst inefficiencies is asymmetric, and that analyst forecasts are more inefficient that market pricing. To further examine this conclusion, we now turn to the earnings-return association test, which can also help to distinguish the four scenarios.

In the contemporaneous regressions of market returns on earnings surprises, analyst earnings forecast is a noisy proxy for the market's earnings expectation due to different degrees of inefficiency. If untreated, this measurement noise will bias the regression coefficients toward zero and generate a smaller R^2 value. To partially alleviate

[12] We note that the average size adjusted abnormal returns are positive in our sample. This is due to the fact that our sample firms are larger than the average firm in the CRSP universe, and in the sample period between 1989 and 2000, larger firms performed better than smaller firms.

this problem, we can remove the predictable component analyst forecast errors from the RHS. If, as suggested by the prediction test, the idiosyncratic component of analyst inefficiency is relatively large with respect to the common component, the signal to noise ratio is likely to be favorable, and as a result both the *ERC* and R^2 should go up. The evidence in Table 7 is consistent with this conjecture. In panel A, we report the year-by-year OLS cross-sectional regressions of annual size-adjusted returns on annual earnings surprises, and contrast those with regressions where the earning expectations are adjusted by our prediction model. While for unadjusted earnings forecasts, the mean *ERC* for 12 annual regressions is 1.774 and the mean R^2 value is 0.079; the estimates for the model adjusted regressions are higher, with mean coefficient value of 2.133 and mean R^2 value of 0.091. In panel B, we test the statistical significance between the two sets of estimates by following Fama and McBeth (1973) and treat each annual estimate as an independent draw. While both ERC and R^2 are higher for the adjusted regression, the difference in *ERC* is more significant statistically.

(Insert Table 7 about here)

Reversing the order of analysis, in Table 8, we conduct reverse earnings-return regressions where annual earnings surprise is the dependent variable and the contemporaneous abnormal return is the independent variable. In this case, the same measurement error problem will arise if the idiosyncratic component for market inefficiency is substantial, a condition not likely to hold as suggested by our prediction test. If we nonetheless repeat the same procedure and remove the predictable component of abnormal returns from the RHS, the resulting regression coefficient and R^2 value may even decrease because the common component of inefficiency is removed from the RHS

but not the LHS. We find this is indeed the case: while for the unadjusted regressions the mean coefficient is 0.035 and the mean R^2 value is 0.083, they decrease to 0.032 and 0.072 for the adjusted regressions. A Fama-McBeth type statistical analysis suggests that the differences in both the coefficient estimate and R^2 values are highly significant (Panel B). This asymmetry in result mirrors that in the prediction test, and is consistent with the notion that beyond a common component of inefficiency, analyst exhibit additional inefficiency absence in market pricing.

5. Conclusions

In this paper we have examined the relation between market and analyst forecast inefficiencies using a prediction test and an association test. In the prediction test, we use a common set of public information to forecast future size-adjusted abnormal returns and analyst forecast errors, and find predictabilities in both. More notably, we find the predictable forecast errors are not associated with future abnormal returns and, yet, the predictable component of abnormal returns is positively associated with future forecast errors.

In the association test, we conduct contemporaneous regressions of stock returns on analyst forecast errors. We find significant increase in regression coefficient estimates and R^2 values when analysts' earnings forecasts are adjusted by removing the predictable component of analyst forecast errors. However, in the reverse regression, we find that adjusting the beginning-of-period market prices by removing the predictable component in market returns does not generate similar results. We conclude that both the prediction

test and the association test imply analysts' forecasts embed more inefficiency that that in market pricing.

This conclusion has important implications for both academic research and practice. It lends support to the growing practice in market anomaly studies that use predictability in analyst forecast errors to discriminate risk versus inefficiency explanations for documented predictability in abnormal returns. Moreover, it also suggests that, in order to exploit the potential inefficiencies in market prices, one is more likely to be successful by predicting future abnormal returns directly rather than building a strategy around predictable analyst forecasts errors, because the latter may contain unique analyst inefficiencies that can act as measurement noise to bias the estimated relation towards zero.

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TABLE 1

Descriptive Characteristics of Sample Variables

The sample contains 15,409 firm-year observations between 1984 and 2003, representing all firms in *I/B/E/S* consensus tape with available data in *CRSP* and *COMPUSTAT*. *Error* is consensus (median) analyst forecast error for the upcoming annual earnings, measured one month after the most recent annual earnings announcement. *Fret* is size-adjusted future abnormal stock return, accumulated in the 13 months after the measurement of *Error*. *MV* is market value. *Cover* is analyst coverage, defined as the number of all analysts who issued earnings forecasts for the upcoming year. *Acc* is the amount of accounting accruals in the most recent annual earnings, measured as the change in non-cash current assets minus depreciation and the change in current liabilities, excluding the current portion of long-term debts and tax payables. *B/P* is book-to-market, which is book value per share from the most recent balance sheet over the stock price. *E/P* is analysts' earnings forecast for the two-year-ahead annual earnings over stock price. *Ltg* is analyst long-term EPS growth rate forecast. *Ltsg* is the annualized long-term sales growth rate in the past five years. *ΔPPE* and *ΔOLA* are the changes of property, plant and equipment and other long-term assets from the previous year. *UE* is the earnings surprise for the most recent quarter. *Ret* is raw stock return in the past 12 months before the measurement of *Error*. *Rev* is revision of the consensus analysts' forecast during the 3 months before the measurement of *Error*. *Error*, *UE* and *Rev* are standardized by current stock price, while *Acc, ΔPPE* and *ΔOLA* are standardized by the average total asset in the nearest two years. *MV*, *Ltg* and stock price are measured at the same time as *Error*.

Panel A: Distributional Statistics

Variable	*Mean*	*Standard Deviation*	*1st Percentile*	*25th Percentile*	*Median*	*75th Percentile*	*99th Percentile*
Error	-0.024	0.507	-0.305	-0.021	-0.003	0.003	0.072
Fret	0.024	0.609	-0.911	-0.264	-0.040	0.199	1.955
MV	3,859	14,295	25	270	833	2,554	57,507
Cover	19.641	13.711	2.000	9.000	16.000	28.000	61.000
Acc	-0.035	0.077	-0.229	-0.071	-0.039	-0.003	0.193
B/P	0.515	0.480	-0.130	0.286	0.459	0.680	1.806
E/P	0.083	0.063	-0.023	0.063	0.081	0.101	0.201
Ltg	0.148	0.077	0.023	0.100	0.140	0.185	0.400
Ltsg	0.146	0.183	-0.127	0.046	0.105	0.198	0.813
ΔPPE	0.036	0.087	-0.166	0.000	0.022	0.057	0.350
ΔOLA	0.031	0.093	-0.122	-0.003	0.008	0.038	0.415
UE	-0.006	0.115	-0.113	-0.002	0.000	0.001	0.021
Ret	0.198	0.594	-0.655	-0.095	0.122	0.363	2.158
Rev	-0.005	0.038	-0.079	-0.003	0.000	0.000	0.015

Panel B: Pooled Cross-Sectional Correlation. Pearson Correlations are below the Main Diagonal, and Spearman Correlations are above the Main Diagonal

	Error	*Fret*	*MV*	*Cover*	*Acc*	*B/P*	*E/P*	*Ltg*	*Ltsg*	*ΔPPE*	*ΔOLA*	*UE*	*Ret*	*Rev*
Error		0.437	0.188	0.082	-0.066	-0.221	-0.197	-0.027	-0.020	-0.040	-0.006	0.249	0.295	0.278
Fret	0.036		0.052	0.048	-0.088	-0.009	0.009	-0.045	-0.019	-0.060	-0.044	0.037	0.054	0.031
MV	0.011	-0.003		0.746	-0.061	-0.344	-0.259	-0.199	-0.120	0.046	0.112	0.055	0.202	0.157
Cover	0.012	0.002	0.388		-0.113	-0.089	-0.105	-0.240	-0.088	0.035	0.026	-0.040	0.021	0.010
Acc	0.017	-0.083	-0.035	-0.103		-0.054	0.059	0.164	0.185	0.142	0.117	0.010	0.017	0.037
B/P	-0.041	0.017	-0.116	-0.059	-0.025		0.532	-0.412	-0.221	-0.103	-0.115	-0.108	-0.368	-0.238
E/P	-0.358	-0.020	-0.088	-0.050	0.049	0.167		-0.298	-0.144	-0.016	-0.075	-0.033	-0.279	-0.096
Ltg	0.005	0.037	-0.001	-0.203	0.153	-0.214	-0.158		0.588	0.208	0.107	0.036	0.084	0.064
Ltsg	0.002	0.042	0.005	-0.073	0.151	-0.109	-0.095	0.501		0.313	0.144	0.023	0.035	0.066
ΔPPE	0.023	-0.034	0.004	-0.003	0.069	-0.039	0.001	0.166	0.247		0.182	0.006	0.024	0.045
ΔOLA	0.010	-0.025	0.084	-0.015	0.093	-0.056	-0.056	0.162	0.192	0.137		-0.019	0.029	0.032
UE	0.731	-0.035	0.013	0.010	0.069	-0.044	-0.243	0.009	0.005	0.048	0.025		0.220	0.270
Ret	0.030	0.002	0.063	-0.020	0.024	-0.223	-0.133	0.179	0.088	0.031	0.062	0.050		0.401
Rev	0.400	-0.001	0.026	0.009	0.059	0.016	-0.185	0.023	0.019	0.057	0.025	0.340	0.109	

TABLE 2

In-sample Pooled LAD Regressions of Analyst Forecast Errors on Prediction Variables

The dependent variable is consensus (median) analyst forecast error for the upcoming annual earnings deflated by the stock price on the forecast date. The independent variables are: accounting accruals (*Acc*), book to price ratio (*B/P*), forward earnings to price ratio (*E/P*), analysts' long term EPS growth rate forecast (*Ltg*), annualized sales growth rate in the past 5 years (*Ltsg*), changes of property, plant and equipment and other long-term assets in the previous year (*ΔPPE* and *ΔOLA*), earnings surprise for the most recent quarter (*UE*), stock return for the past 12 months (*Ret*) and revision of analysts' two-year-out forecasts in the past 3 months (*Rev*). Detailed definitions of variables are in Section 3. T-statistics are reported underneath coefficient estimates.

Intercept	*Acc*	*B/P*	*E/P*	*Ltg*	*Ltsg*	*ΔPPE*	*ΔOLA*	*UE*	*Ret*	*Rev*
-0.004	-0.016									
(-25.24)	(-8.59)									
0.017		-0.0148	-0.115	-0.043	0.001	-0.004	-0.001			
(43.70)		(-54.00)	(-55.68)	(-21.84)	(0.67)	(-2.70)	(-0.57)			
-0.004								0.446	0.005	0.720
(-29.05)								(395.40)	(22.08)	(212.3)
0.013	-0.010	-0.009	-0.098	-0.041	-0.000	-0.009	-0.001	0.416	0.003	0.662
(34.40)	(-6.26)	(-36.20)	(-49.30)	(-22.10)	(-0.07)	(-6.04)	(-0.44)	(371.3)	(15.92)	(199.7)

TABLE 3

Out-of-sample Forecasting of Analyst Forecast Errors

In each year, we first estimate the full model using data from the past five years, and then apply the estimated coefficients (insignificant coefficients are set to zero) to the current values of the prediction variables to predict the forecast errors. In Panel B, analyst forecasts are adjusted by adding predicted forecast errors to the IBES consensus. Definitions: *MSE* is *M*ean *S*quared *E*rror, *MAD* is *M*ean *A*bsolute *D*eviation, *MSE Reduction* is measured as (*MSE of OLS Adjusted Error/MSE of Actual Error-1)*100*, *LAD Reduction* and *Std. Dev. Reduction* are likewise defined.

Year	*N*	*Mean*	*Median*	*Std. Dev.*	*Std. Dev. Reduction*	*MSE*	*MSE Reduction*	*MAD*	*MAD Reduction*
Panel A: Distribution Unadjusted Analyst Forecast Errors									
1989	766	-0.0253	-0.0074	0.0672	-	0.0051	-	0.0319	-
1990	807	-0.0295	-0.0083	0.1159	-	0.0143	-	0.0375	-
1991	951	-0.0219	-0.0039	0.1202	-	0.0149	-	0.0290	-
1992	986	-0.0171	-0.0038	0.0565	-	0.0035	-	0.0238	-
1993	1,057	-0.0110	-0.0007	0.0521	-	0.0028	-	0.0207	-
1994	1,037	-0.0123	-0.0011	0.0716	-	0.0053	-	0.0243	-
1995	1,066	-0.0136	-0.0018	0.0503	-	0.0027	-	0.0224	-
1996	1,106	-0.0100	-0.0009	0.0489	-	0.0025	-	0.0189	-
1997	1,162	-0.0178	-0.0044	0.0982	-	0.0099	-	0.0234	-
1998	1,174	-0.0151	-0.0005	0.0722	-	0.0054	-	0.0315	-
1999	1,132	-0.0140	-0.0008	0.0812	-	0.0068	-	0.0327	-
2000	1,097	-0.0376	-0.0112	0.1833	-	0.0350	-	0.0420	-
Mean		-0.0188	-0.0037	0.0848	-	0.0090	-	0.0282	-
Panel B: Distribution of LAD Adjusted Analyst Forecast Errors									
1989	766	-0.0154	-0.0026	0.0607	9.68	0.0039	23.98	0.0278	12.78
1990	807	-0.0161	-0.0033	0.1106	4.50	0.0125	12.53	0.0333	11.19
1991	951	-0.0133	-0.0023	0.0937	22.07	0.0089	40.05	0.0258	11.13
1992	986	-0.0093	-0.0008	0.0518	8.38	0.0028	20.63	0.0209	11.94
1993	1,057	-0.0025	0.0035	0.0514	1.44	0.0026	6.78	0.0206	0.45
1994	1,037	-0.0031	0.0035	0.0654	8.67	0.0043	18.80	0.0230	5.22
1995	1,066	-0.0073	-0.0003	0.0447	11.28	0.0020	24.65	0.0202	9.75
1996	1,106	-0.0034	0.0009	0.0465	4.94	0.0022	12.83	0.0192	-1.93
1997	1,162	-0.0139	-0.0038	0.0825	16.02	0.0070	29.77	0.0209	10.78
1998	1,174	-0.0067	0.0011	0.0744	-3.11	0.0056	-2.67	0.0303	4.04
1999	1,132	-0.0079	-0.0008	0.0786	3.26	0.0062	8.20	0.0316	3.31
2000	1,097	-0.0261	-0.0071	0.1099	40.05	0.0127	63.57	0.0338	19.57
Mean		-0.0104	-0.0010	0.0725	14.50	0.0059	34.63	0.0256	9.06

TABLE 4
The Sources of Improvement

Panel A reports the distribution of forecast errors of decile portfolios sorted by the predicted forecast errors. *Improvement* is calculated as (MAD of adjusted forecast/MAD of actual forecast –1) *100. *% Improved* is the frequency with which LAD adjusted forecasts are more accurate than actual forecasts. Panel B reports portfolio characteristics of the decile portfolios. The independent variables are: market capitalization (*MV*), analyst coverage (*Cover*), accounting accruals (*Acc*), book to price ratio (*B/P*), forward earnings to price ratio (*E/P*), analysts' long term EPS growth rate forecast (*Ltg*), annualized sales growth rate in the past 5 years (*Ltsg*), changes of property, plant and equipment and other long-term assets in the previous year (*ΔPPE* and *ΔOLA*), earnings surprise for the most recent quarter (*UE*), stock return for the past 12 months (*Ret*) and revision of analysts' two-year-out forecasts in the past 3 months (*Rev*). Detailed definition of variables is in Section 3.

Panel A: Forecast Improvement in Decile Portfolios, Sorted by the Value of Forecasted Error

	Mean Adj Error	*Med. Adj. Error*	*Mean Error*	*Med. Error*	*Improve- ment*	*% Improved*
1	-0.049	-0.031	-0.092	-0.047	15.60	67.30
2	-0.016	-0.016	-0.035	-0.022	13.50	67.10
3	-0.010	-0.011	-0.023	-0.012	9.10	63.10
4	-0.007	-0.008	-0.015	-0.006	6.30	57.90
5	-0.005	-0.005	-0.008	-0.003	4.40	55.50
6	-0.003	-0.004	-0.006	-0.001	1.30	52.40
7	-0.002	-0.002	-0.005	-0.001	0.50	50.20
8	0.000	0.000	-0.002	0.000	-0.60	49.30
9	0.002	0.002	0.000	0.000	-2.30	44.40
10	0.009	0.005	-0.001	0.002	-6.70	43.70

Panel B: Characteristics of Decile Portfolios, Sorted by the Value of the Forecasted Error

	MV	*Cover*	*Acc*	*BP*	*EP*	*Ltg*	*Ltsg*	*ΔPPE*	*ΔOLA*	*UE*	*Ret*	*Rev*
1	580	13	-0.044	0.949	0.113	0.16	0.17	0.035	0.017	-0.040	-0.255	-0.035
2	1,104	15	-0.022	0.732	0.103	0.17	0.18	0.049	0.032	-0.003	-0.112	-0.007
3	1,557	15.9	-0.024	0.613	0.094	0.16	0.17	0.052	0.038	-0.001	-0.021	-0.003
4	2,216	17.6	-0.025	0.542	0.088	0.15	0.16	0.046	0.036	0.000	0.052	-0.002
5	2,731	18.6	-0.029	0.474	0.082	0.15	0.15	0.043	0.035	0.000	0.124	-0.001
6	4,167	20.2	-0.032	0.441	0.077	0.14	0.14	0.038	0.040	0.000	0.184	0.000
7	5,452	20.7	-0.039	0.387	0.073	0.14	0.14	0.032	0.033	0.000	0.256	0.000
8	6,420	21.6	-0.040	0.354	0.068	0.14	0.13	0.028	0.037	0.001	0.351	0.000
9	9,697	22.9	-0.044	0.299	0.062	0.15	0.14	0.026	0.034	0.001	0.495	0.001
10	7,239	19.9	-0.061	0.240	0.052	0.16	0.16	0.016	0.027	0.004	0.954	0.004

TABLE 5

Forecasting Future Size-adjusted Returns

In each year, we first estimate the full model using data from the past five years. The dependent variable is the size-adjusted abnormal return for 13 months starting one month after the release of annual earnings. The independent variables are the same as those used in Table 2. We then apply the estimated coefficients (insignificant coefficients are set to zero) to the current values of the prediction variables to predict the abnormal returns for the next 13 months. We form five quintile portfolios based on the predicted abnormal return. From portfolio 1 to portfolio 5, the predicted returns increase.

Panel A: In-sample regression coefficients

	Intercept	*Acc*	*B/P*	*E/P*	*Ltg*	*Ltsg*	*ΔPPE*	*ΔOLA*	*UE*	*Ret*	*Rev*
Mean	0.010	-0.199	-0.005	-0.312	-0.144	-0.009	-0.177	-0.043	0.189	0.063	0.033
T	(1.19)	(-27.52)	(-0.89)	(-4.02)	(-2.64)	(-0.67)	(-5.32)	(-2.33)	(3.14)	(7.07)	(0.25)

Panel B: Future abnormal returns

Year	*1*	*2*	*3*	*4*	*5*	*(5-1)*
1989	0.041	-0.041	-0.010	0.048	0.139	0.098
1990	-0.011	-0.017	-0.051	0.015	0.018	0.029
1991	0.022	0.009	0.026	-0.010	0.007	-0.015
1992	-0.057	0.026	0.003	0.056	0.141	0.198
1993	-0.088	-0.001	0.008	0.034	0.057	0.145
1994	-0.092	-0.086	-0.042	-0.035	0.082	0.174
1995	-0.101	-0.036	0.013	-0.021	-0.012	0.089
1996	-0.090	-0.077	-0.020	-0.026	0.054	0.144
1997	-0.195	-0.131	-0.061	-0.074	-0.052	0.143
1998	0.037	0.066	-0.173	-0.144	0.231	0.195
1999	0.223	0.335	0.374	0.293	0.278	0.055
2000	0.203	0.186	0.166	0.151	0.027	-0.176
Average	-0.009	0.019	0.020	0.024	0.081	0.090

TABLE 6

The Relation between the Predictable Abnormal Returns and the Predictable Forecast Errors

In Panel A, we form decile portfolios based on predicted abnormal returns as defined in Table 5. *Error1* is the realized analyst forecast error for the upcoming annual earnings, and *Error2* is the realized analyst forecast error for two-year-ahead annual earnings. In Panel B, we form decile portfolios based on predicted analyst earnings forecasts for the upcoming fiscal year. *Fret4* and *Fret13* are the size-adjusted abnormal returns for the 4 months and 13 months after portfolio formation respectively.

Panel A: Portfolios sorted on predicted future abnormal returns

Rank	*Error1*	*T-Stat*	*Error2*	*T-Stat*
1	-0.039	-9.524	-0.057	-8.293
2	-0.020	-11.093	-0.034	-8.435
3	-0.013	-5.469	-0.023	-7.263
4	-0.009	-3.130	-0.020	-4.926
5	-0.012	-2.273	-0.019	-5.295
5-1	0.027	3.792	0.038	5.020

Panel B: Portfolios sorted on predicted analyst forecast errors

Rank	*Fret4*	*T-Stat*	*Fret13*	*T-Stat*
1	0.021	1.542	0.039	0.989
2	0.015	1.350	0.004	0.085
3	0.022	2.454	0.015	0.519
4	0.020	1.947	0.018	0.563
5	0.035	2.838	0.059	2.662
5-1	0.014	1.046	0.020	0.667

TABLE 7

Analyst Forecasts as Noisy Proxies for Market Earnings Expectations

In each year, we first estimate the full model using data from the past five years, and then apply the estimated coefficients (insignificant coefficients are set to zero) to the current values of the prediction variables to predict the forecast errors and adjust the raw analyst forecasts. We then run contemporaneous annual return-earnings regressions, with the earnings expectations measured as a) the IBES consensus forecasts and b) the IBES consensus forecasts adjusted for the predicted errors.

	Raw Forecast Errors			*Model-adjusted Forecast Errors*		
Panel A: Yearly estimation of the regression coefficients						
	Intercept	*ERC*	R^2	*Intercept*	*ERC*	R^2
1989	0.081	1.738	0.078	0.069	2.131	0.094
1990	0.024	1.150	0.085	0.011	1.361	0.108
1991	0.023	0.723	0.048	0.021	1.044	0.060
1992	0.067	1.715	0.056	0.055	1.949	0.061
1993	0.032	2.359	0.136	0.012	2.438	0.142
1994	-0.011	2.329	0.137	-0.032	2.706	0.162
1995	0.008	2.663	0.115	-0.004	3.320	0.140
1996	0.001	3.114	0.107	-0.018	3.519	0.123
1997	-0.092	0.750	0.024	-0.092	0.970	0.028
1998	0.053	2.839	0.019	0.033	3.592	0.031
1999	0.345	3.109	0.113	0.327	3.450	0.129
2000	0.100	-1.156	0.081	0.120	-0.889	0.015
Mean	0.052	1.778	0.083	0.042	2.133	0.091
Panel B: Differences and statistical significance of mean coefficient estimates and R^2						
	Intercept	*ERC*	R^2			
Mean Difference	0.011	-0.355	-0.01			
T-Stat	(3.16)	(-6.50)	(-1.12)			

TABLE 8

Reverse Regression: Measurement Noise In Market Prices?

In each year, we first estimate the return prediction model using data from the past five years, and then apply the estimated coefficients (insignificant coefficients are set to zero) to the current values of the prediction variables to predict the abnormal returns for the next 13 months and adjust the realized abnormal returns accordingly. We then run contemporaneous annual reverse return-earnings regressions, with the actual abnormal returns or the adjusted abnormal return as the independent variables.

	*UE= $\alpha + \beta$ * Abnormal Return*			*UE= $\alpha + \beta$ * Adjusted Abnormal Return*		
	Intercept	*Coefficient*	*R^2*	*Intercept*	*Coefficient*	*R^2*
Panel A: Yearly estimation of the regression coefficients						
1989	-0.028	0.045	0.078	-0.028	0.040	0.065
1990	-0.029	0.074	0.085	-0.031	0.071	0.078
1991	-0.023	0.066	0.048	-0.023	0.062	0.041
1992	-0.019	0.033	0.056	-0.019	0.030	0.045
1993	-0.011	0.058	0.136	-0.013	0.055	0.124
1994	-0.009	0.057	0.129	-0.012	0.056	0.125
1995	-0.012	0.043	0.115	-0.014	0.038	0.090
1996	-0.009	0.034	0.107	-0.011	0.033	0.100
1997	-0.014	0.032	0.024	-0.016	0.028	0.018
1998	-0.015	0.007	0.019	-0.016	0.007	0.019
1999	-0.025	0.036	0.113	-0.027	0.029	0.078
2000	-0.026	-0.070	0.081	-0.020	-0.068	0.076
Mean	-0.018	0.035	0.083	-0.019	0.032	0.072
Panel B: Differences and statistical significance of mean coefficient estimates and R^2						
	Intercept	*Coefficient*	*R^2*			
Mean Difference	0.001	0.003	0.011			
T-Stat	(1.16)	(4.24)	(3.92)			