

Forecasting Analysts' Forecast Errors

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Abstract

In this paper, we examine whether analysts' forecasts errors are predictable out of sample. Following market efficiency studies by Ou and Penman (1989) and Lev and Thiagarajan (1993), we employ a comprehensive list of forecasting variables. Our estimation procedures include the traditional OLS as well as a more robust procedure that minimizes the sum of absolute errors (LAD). While in-sample we find significant prediction power using both OLS and LAD, we find far stronger results using LAD out of sample, with an average reduction in forecast errors of over thirty percent measured by the mean squared error or near ten percent measured by the mean absolute error. Most of the prediction power comes from firms whose forecasts are predicted to be too optimistic. The stock market seems to understand the inefficiencies in analyst forecasts: a trading strategy based on the predicted analyst forecast errors does not generate abnormal profits. Conversely, analysts seem to fail to understand the inefficiencies present in the stock prices: a trading strategy directly based on the predicted stock returns generates significant abnormal returns, and the abnormal returns are associated with predictable analyst forecast errors. The combined evidence suggests that the stock market is more efficient than financial analysts in processing public information.

1. Introduction

A large number of studies in accounting and finance find that analysts use information inefficiently in forecasting future earnings. Analyst earnings forecasts are found to be too optimistic (O'Brien [1988], Francis and Philbrick [1993], Easterwood and Nutt [1999]), over-react to some information (De Bondt and Thaler [1990], La Porta [1996], Frankel and Lee [1998]), and under-react to some other information (Mendenhall [1991], Lys and Sohn [1990], Abarbanell and Bernard [1992], Liu [2004]). The reasons for the inefficiencies have been attributed to conflict of interests between investment banking and primary research (e.g., Francis and Philbrick [1993], Alford and Berger [1997]), reporting or selection biases (e.g., Francis and Philbrick [1993], Lin and McNichols [1998]), and cognitive biases (e.g., De Bondt and Thaler [1990], Abarbanell and Bernard [1992]).

Some recent studies challenge the inefficiency conclusion reached in prior literature. Keane and Runkle [1998] argue that prior studies overstated statistical significance levels by not fully accounting for the cross-sectional correlation among forecast errors. Gu and Wu [2003] hypothesize that analysts' loss function is to minimize the mean of absolute errors (least absolute error, or LAD), suggesting the median, instead of the mean, as the optimal forecaster. Their evidence suggests that analysts are not in fact too optimistic if this alternative loss function is adopted. Along similar lines, Basu and Markov [2004] show that the over-reaction result of De Bondt and Thaler [1990] and the under-reaction result of Abarbanell and Bernard [1992] are much weaker under LAD, in contrast with the traditional OLS regression.

In this study, we contribute to the debate on the information efficiency of analyst forecasts by examining whether those forecasts can be improved upon ex ante, in out-of-sample tests. Evidence in this regard is important because the prior literature has largely focused on in-sample analysis, which assumes that analysts can see the whole span of data series generated in the testing period, while in reality at each point in time an analyst can only observe what happened in the past. To the extent that the coefficient estimates conditional on past information vary over time, in-sample fit may not be accompanied by out-of-sample forecasting performance.¹ In addition, while in in-sample analysis there is often room for debate about the appropriate ways to measure the significance levels of the estimates without knowing the true values of the parameters being estimated (e.g., Keane and Runkle [1998]), in out-of-sample forecasting, the performance of the model can be more objectively measured because we observe the actual realizations of the forecasted variables.

To accommodate the possibility that analysts' loss function may involve minimizing the sum of the absolute forecast errors, our estimation procedures include LAD as well as the traditional OLS. In addition to the benefit of correcting potential mechanical biases caused by using an inappropriate loss function, LAD has the advantage of generating more robust estimation than OLS. Unlike OLS estimation, which is heavily influenced by extreme observations in the sample, LAD belongs to a class of robust estimators that assign less weight to extreme observations, implying that LAD is more likely to produce stable coefficient estimates than OLS, an important consideration in out-of-sample forecasting.

¹ For example, a recent paper by Goyal and Welch [2003] find that dividend to price ratios do not predict future returns out of sample, in contrast with the strong in-sample results.

In contrast with prior research that considers a small set of variables with which analysts may exhibit inefficiency, we simultaneously analyze a comprehensive list of forecasting variables.² This approach is similar to that adopted by Ou and Penman [1989] and Lev and Thiagarajan [1993], who study stock market inefficiency. Our forecasting variables are primarily motivated by prior in-sample studies that document analyst inefficiency. We also include some variables with which the stock market is found to exhibit inefficiency because of the close link between stock prices and analysts' earnings forecasts (Liu and Thomas [2000], Liu Nissim and Thomas [2002]). Specifically, the forecasting variables we consider 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).³

We find reliable evidence that financial analysts use information inefficiently in forecasting future earnings. In in-sample analysis, no matter whether OLS or LAD is used, all prediction variables except sales growth and investments in other long-lived assets are statistically significant in forecasting future earnings surprises. In out-of-sample prediction analysis, we modify analysts' forecasts using the predicting variables and coefficients estimated using several configurations of past data, and compare the accuracy and precision of the modified forecasts with those of the original forecasts. In

² Prior research such as Ali, Klein and Rosenfeld [1992] and Basu and Markov [2003] also provide some out-of-sample forecasting results using OLS and a small set of forecasting variables.

³ We motivate these forecasting variables in section 2.1. Prior studies that examine these variables in isolation include Mendenhall [1991] (earnings surprise), Abarbanell [1991] (stock returns), La Porta [1996] (long term growth forecasts), Frankel and Lee [1998] (book to price ratio, forward earnings to price ratio) and Bradshaw, Richardson and Sloan [2001] (accrual component of earnings). Investments in property, plant and equipment and other long-lived assets is motivated by Titman, Wei and Xie's [2001] finding that the stock market overreacts to growth in firms' investments.

this case, LAD generates far stronger results than OLS. While the OLS prediction results are not stable, with the adjusted forecasts performing better than the unadjusted forecasts in some years, but worse in some other years, the LAD results are robust, generating improvement over unadjusted forecasts in eleven out of the twelve years examined. The average improvement based on LAD is over thirty percent measured by mean squared error and almost ten percent measured by mean absolute error.⁴ Putting the evidence together, our results suggest that analysts' information inefficiency is a robust phenomenon; they also demonstrate the merit of using robust estimators such as LAD in out-of-sample forecasting.

Motivated by Easterwood and Nutt [1999] who document that analysts' information inefficiency is asymmetric with respect to good news versus bad news, we examine the source of the predictability by sorting firms into portfolios based on predicted forecast errors. Consistent with their evidence, we find that large improvement in LAD adjusted forecasts happens only in portfolios that are predicted to reflect analyst optimism, while there is little improvement on the pessimism side. Further analysis shows that the improved portfolios are smaller in size and more thinly covered by analysts.

The fact that analysts react inefficiently to public information raises a natural question as to whether the stock market behaves in similar ways. We examine this issue in two steps. In the first step, we demonstrate that the predicting variables we employ can be used to predict future size adjusted abnormal returns. This finding is not surprising

⁴ Given that LAD minimizes the mean absolute deviation, the reduction in the mean absolute error is to some extent expected. The large reduction in the mean squared error is somewhat surprising. We further note that OLS based prediction performs poorly using either mean absolute error or mean squared error as a gauge.

because similar results have been documented by univariate tests in prior research. In the second step, we investigate whether the analyst and market inefficiencies are related. We find that the stock market seems to understand the inefficiencies contained in analyst forecasts: a trading strategy based on the predicted analyst forecast errors does not generate abnormal profits. In addition, when we compare regressions of abnormal returns on contemporaneous earnings forecast errors, separately based on analysts' original forecasts and forecasts adjusted by our prediction model, the latter regressions have higher response coefficients and R^2 values. Conversely, analysts seem to fail to understand the inefficiencies present in the stock prices: a trading strategy directly based on the predicted stock returns generates significant abnormal returns, and the abnormal returns are associated with predictable analyst forecast errors. This evidence is consistent with prior research that shows market anomalies are related to analysts' inefficiencies (e.g., Abarbanell and Bernard [1992] and Bradshaw et al [2001]). The combined evidence suggests that the stock market is more efficient than financial analysts in processing public information.

The rest of the paper is organized as follows: section 2 describes our research design, where we motivate the prediction variables and discuss regressions based on LAD; section 3 describes our sample; section 4 presents the empirical results and section 5 concludes the paper.

2. Research design issues

2.1 Forecasting variables

Similar to Ou and Penman [1989] and Lev and Thiagarajan [1993] who study stock market efficiency, we employ a comprehensive list of publicly available information variables to predict analysts' forecast errors. Our forecasting variables are primarily motivated by prior literature that documents in-sample analyst inefficiency. We also include variables with which the stock market is found to exhibit inefficiency because of the close link between stock prices and analysts' earnings forecasts.

Specifically, we consider three "under-reaction" variables and seven "overreaction" variables. 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). These papers find that analysts react sluggishly to new information contained in quarterly earnings surprises, stock returns or analysts' earnings forecast revisions. Similar sluggish reaction has been found for market returns with respect to the three under-reaction variables.

The seven over-reaction variables are motivated by the string of research that finds the stock market over-reacts to certain public information variables. The first set of over-reaction variables have been considered by Frankel and Lee [1998] in their attempt to build a trading strategy based on the difference between fundamental values and stock prices. The variables they use to predict analysts' inefficiency include book to price ratio, forward earnings to price ratio, past sales growth and analysts' long term earnings forecasts. Among these variables, book to price ratio and forward earnings to price ratio

have been studied extensively in the literature. Past sales growth is motivated by the finding of La Porta [1996] 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 growth forecasts has been studied 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. Since stock prices are highly correlated with forward earnings (Liu and Thomas [2000], Liu, Nissim and Thomas [2002]), the fact that the level of long term growth forecasts can help to predict future returns suggests that it may also help to predict earnings surprises.⁵

We adopt the accrual component of earnings as an “over-reaction” forecasting variable because Sloan [1996] and a number of subsequent papers find that the stock market seems to over-react to accounting accruals compared with cash flows, and accruals deflated by total assets are negatively correlated with future abnormal returns. In addition, Bradshaw et al [2002] find that analysts and auditors also fail to understand the differential implications of accounting accruals versus cash flows for future earnings.

The remaining variables are motivated by a recent study by Titman, Wei and Xie [2001], 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

⁵ 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.

negative abnormal returns because of increased investments in negative net present value capital expenditures.

2.2. *Estimation and forecast procedure*

To predict analyst forecast errors out of sample, in each year, one month after the release of annual earnings,⁶ 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 error for the upcoming year. 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 the alternative Least Absolute Deviation (LAD) procedure. Similar to OLS, LAD assumes a linear relation between the dependent variable 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. OLS is often interpreted as estimating the expectation of y conditional on x , i.e.,

$$E(y_i | x_i) = \beta x_i.$$

The beta coefficients in OLS are estimated by minimizing the sum of squared residuals, that is

⁶ We also tried forecasts at two or three months after earnings announcements. The results are very similar.

$$\min_{\beta} \sum_i \varepsilon_i^2 .$$

Similarly, LAD can be interpreted as estimating the median of y conditional on x , i.e.,

$$MEDIAN(y_i | x_i) = \beta x_i .$$

And the coefficients can be estimated by minimizing the sum of absolute residuals, that is

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

Comparing LAD with OLS, it is clear that LAD assigns less weight to extreme observations than OLS does. Therefore, it is more robust to variation in sample realizations. For this reason, it is often classified as an example of robust estimators (Kennedy [2003]). On the other hand, because LAD is less sensitive to the magnitude of the variables used in estimation, it uses information less efficiently than OLS. The tradeoff between robustness and information is an empirical issue.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

⁷ 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.

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.

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.

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.

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.

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 percent 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 [2002]). 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 [2001] 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.

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*.

4. Results

4.1 In-sample results

Table 2 presents the in-sample pooled regression results. Panel A reports results estimated using OLS procedure and Panel B reports results estimated using 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]).

(Insert Table 2 about here)

The first row of Panel A presents the simple regression results based on accounting accruals. Opposite to findings by Bradshaw et al [2001], we find that the regression coefficient is positive, though barely significant at conventional levels, suggesting that analysts are under-reacting to accruals, instead of over-reacting. However, we note that this difference could be due to non-linearity or outliers. These issues are significant in our case since we use OLS regression, but may be mitigated by forming portfolios as in Bradshaw et al [2001]. The first row of Panel B replicates this simple regression using LAD. The resulting regression coefficient is reliably negative (-0.016) with t-statistics of -8.59, confirming the results based on portfolios. The fact that LAD regression and portfolio analysis generate consistent results that are opposite to that generated under OLS is consistent with the econometric prediction that LAD is more robust than OLS.

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 in either OLS or LAD regression. The results on the under-reaction variables are also consistent with prior research. In LAD regressions, all coefficients are significantly positive, implying analysts' under-reactions. However, in OLS regressions, the coefficient on past returns (*Ret*) is negative. This could be caused by the fact that highly correlated variables like *UE* and *Rev* are included in the same regression. A striking feature of the regression based on the under-reaction variables is that the R^2 value is quite high, with a value of 56%. This suggests that, in sample, a large portion of the variation in analyst forecast errors are predictable. Moving to the full model, where all prediction variables are included, we find that regression results based on each individual group is largely preserved. In LAD regression, with the exception that *Ltsg* and ΔOLA are not statistically significant, all over-reaction (under-reaction) variables have significant negative (positive) coefficients.

To summarize, results in Table 2 are consistent with the notion that analysts' forecasts are inefficient in using publicly available information. Our results raise two natural questions. First, as noted in the introduction, as a matter of statistical principle, in sample fit does not guarantee out-of-sample prediction power. Although we obtain high R^2 values for OLS regressions, it is interesting to see whether these high R^2 values directly translate into out-of-sample prediction power. We address this question in section 4.3. Second, our LAD results are consistent with the notion that analysts are inefficient even

under an alternative loss function that minimizes the sum of absolute errors. To reconcile our results with those in Basu and Markov [2004], we now turn to the next section.

4.2 *The effect of forecast horizon on analyst forecast efficiency*

Our in-sample analysis differs from Basu and Markov [2004] in two ways. First, while they examine whether analysts' forecasts efficiently incorporate information in past returns and earnings, we consider a broader set of prediction variables. This difference, though substantial, is not the cause for the difference in our results, because we obtain significant results when we only consider sub-groups of prediction variables. Second, in our analysis, analyst forecasts and the prediction variables are measured one month after the earnings announcement of the prior fiscal year, therefore our forecast horizon is one year. Basu and Markov [2004] also investigate annual earnings forecasts, but they measure analysts' forecasts over a sixty day window before the actual earnings announcement, resulting in an average forecast horizon of about a month. The difference in the choice for forecast horizon is likely the cause for the difference in empirical results, because by one month before the announcement of annual earnings, inefficiency in annual earnings forecasts is likely to be mostly resolved due to revelation of information throughout the fiscal year.¹⁰

To show that forecast horizon is the major driver for the differences, in Table 3, we repeat the in-sample regressions at shorter horizons. To ease comparison, in Panel A, we repeat the full model analysis as in Table 2.¹¹ In Panel B and C, we measure earnings forecasts and the prediction variables one month after the second quarter earnings

¹⁰ For example, the first three quarterly earnings are known through quarterly reports.

¹¹ Since additional data requirement reduces the sample further, the results in Panel A is slightly different from Table 2.

announcement and one month before the annual earnings release, respectively. As we move from Panel A to B and C, most regression coefficients reduce in magnitudes as well as significance levels. The reduction in magnitude is most dramatic for LAD regressions. At one month before annual earnings release, all variables except *UE* and *Rev* have coefficients close to zero, consistent with findings in Basu and Markov [2004]. We note, however, even at one month before the annual earnings release, several variables such as *B/P*, *E/P*, *Ltg*, *UE*, *Ret* and *Rev* are statistically significant, though their economic significance is difficult to judge without doing out-of-sample prediction.

(Insert Table 3 about here)

Because we are interested in analysts' annual earnings forecasts, in all analyses that follow, we maintain a forecast horizon of one year by measuring analysts' forecasts as well as the prediction variables one month after the annual earnings release of the prior fiscal year.

4.3 *Out-of-sample prediction results*

To predict analysts' forecast errors out of sample, in each year, we first estimate the full model using the past five years of data, then apply the estimated coefficients to the current values of the independent variables to predict the forecast errors. 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 4.

(Insert Table 4 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 scale 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 based on OLS. The results are mixed. On one hand, there is some evidence that the information efficiency of analyst forecasts is improved. Analysts' overall bias is greatly reduced, the average mean forecast error decreases from the unadjusted -0.019 to the adjusted -0.0021, and the average median forecast error decreases from -0.0037 to -0.0005. In eight out of the twelve sample years, there are some reduction in standard deviation and *MSE*, suggesting improved precision in analysts' forecasts. On the other hand, in the remaining four years, there are large increases in standard deviation and *MSE*. As a result, the average dispersion of the forecast errors increases, implying decreased precision in the adjusted forecasts. The result for *MAD* is even worse – OLS based prediction only improve *MAD* in three out of twelve years, and the increases in *MAD* are 208% and 204% in 1989 and 1990, respectively. These mixed out-of-sample prediction results, in contrast with the in-sample statistical significance reported in Table 2, are consistent with the notion that in-sample fit does not guarantee out-of-sample prediction power.

Moving to results on out-of-sample predictions based on LAD (Panel C), the picture changes substantially. Similar to OLS based prediction, analyst forecast bias decreases greatly, to -0.0104 for the mean and -0.0010 for the median. 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%.¹² In the three sample years where OLS generates big forecast errors (1989, 1990 and 1991), LAD predictions all consistently improve analysts' forecasts.

Consistent with the approach adopted by Fama and MacBeth [1973], we test the statistical significance of the prediction result by treating each year's reductions in *MSE* and *MAD* as 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*.

Corroborating the in-sample LAD results reported in Table 2, the out-of-sample prediction results suggest that analysts' earnings forecasts are inefficient in using public available information, even under the alternative loss function assumption that analysts minimize the sum of absolute errors. The superior out-of-sample forecasting results based on LAD are consistent with the notion that LAD generates more robust estimates than the traditional OLS. Given its superior statistical properties, it is surprising that robust estimators such as LAD are not used more often in capital markets research.

4.4 *Explaining the difference between in-sample and out-of-sample results*

What can explain the large difference between the in-sample and the out-of-sample results for OLS but consistency in results for LAD? Econometrically, the difference between in-sample and out-of-sample results will be large (small) if the coefficient estimates conditional on past information is unstable (stable) in time series.

¹² 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.

Therefore, we hypothesize that coefficient estimates under OLS are more variable than those estimates under LAD.

To examine this hypothesis, we first estimate the coefficients on the prediction variables in the same way as in Table 4 using past data. We then estimate the coefficients using each year's contemporaneous data. This step gives us the "best" estimates that fit the data in sample. For example, for test year 1989, we first use data from 1984 to 1988 to estimate coefficients for each forecasting variable as in Table 4, and then use 1989 data to estimate the in-sample coefficients. Finally, we take the difference between these two vectors of coefficient estimates and present the result in Table 5.

(Insert Table 5 about here)

Panel A presents the year by year difference in coefficients for LAD; Panel B presents the same for OLS. Zeros represent situations where the underlying forecasting variables are dropped because they are not statistically significant in estimation using past data. Among all the prediction variables, LTSG and OLA are dropped in almost all years under both LAD and OLS, implying that only the other eight variables are used actively in out-of-sample forecasting.

To gauge how much the predicted coefficients deviate from the best fitting in-sample coefficients, we calculate the standard deviation of each column and present the result in the last row of each panel. For all forecasting variables, the standard deviation is materially larger for OLS than for LAD. This point can be most clearly seen by examining the last row of Table 5, which contains the differences in standard deviation between OLS and LAD. The fact that all differences are positive and with magnitudes

quite large compared with the averages offers strong support to our conjecture that conditional coefficients are more stable under LAD than OLS.

4.5 *Sources of improvement*

In this section we investigate the sources of improvement documented in Table 4. 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 6. The left side of panel reports results based on OLS and the right side of the panel reports results based on LAD. 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 *MSE* after the adjustment, and the frequency at which the adjusted forecasts are more accurate than the unadjusted forecasts.

(Insert Table 6 about here)

For both OLS and LAD based adjustments, 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 both methods offer only partial adjustments because monotonicity is preserved for the adjusted means and medians. Consistent with the general results presented in Table 4, OLS based forecasts actually behave worse than the unadjusted forecasts. For portfolios with negative (positive) forecast errors, the OLS adjustment makes the errors more negative (positive).

Measured by the magnitude of MSE , OLS offers only modest improvement in three of the ten portfolios, but large deterioration in the other seven portfolios. With the exception of portfolio 1, forecast errors for most of the stocks in other portfolios are higher for adjusted forecasts. In portfolio 10, for example, adjustments make 75% of the forecasts less accurate than the unadjusted forecasts. The results for LAD adjustment are markedly better than the OLS results. For seven out of the ten portfolios, LAD 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 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 the ones 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 considerably.

4.6 *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 and only marginally 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 for LAD are essentially not changed, but the results for OLS are worse.

4.7 *Analysts and the stock market*

Our finding that large negative forecast errors are predictable out-of-sample raises a natural question as to whether the stock market behaves in similar manner. We investigate this possibility in two steps. In the first step, we examine whether the stock market reacts inefficiently to public information by using the same set of variables to predict size adjusted stock returns out-of-sample. We expect to find significant prediction power because several variables have been shown to have return prediction power in univariate tests. In the second step, we attempt to see whether the market inefficiency and analyst inefficiency are related by examining if predictable returns are associated with predictable forecast errors and vice versa.

Table 7 presents the results of the first step. Following the same procedure as the out-of-sample prediction of forecast errors, we predict future abnormal returns by simply replacing the forecast errors with size adjusted abnormal returns, measured over 13 months starting one month after the release of earnings for the last fiscal year. The left panel reports OLS results, and the right panel LAD. The results strongly indicate that the stock market does not impound public information efficiently. For OLS based forecasts, in ten out of the twelve sample years, a hedge portfolio that is long in the highest quintile of forecasted returns and short in the lowest quintile generates zero-investment positive returns with an average of 12.5% for the thirteen month period. Results are somewhat different when LAD is used. LAD generates two years of negative hedge returns (hedge

return is virtually zero in 1999), the average return generated by LAD is lower, about 9% for the thirteen-month period. An interesting feature to note is that OLS and LAD seem to generate quite different portfolio formations, because the money losing years using each procedure do not match. In 1999 for example, OLS forecasts generate a -13.5% hedge return, while LAD forecasts generate a positive 5.5% hedge return.

(Insert Table 7 about here)

In Table 8, we investigate whether analyst and market inefficiencies are related. In Panel A, we form quintile portfolios based on predicted abnormal returns. We then examine whether one year out and two year out earnings forecast errors are positively sloped in the portfolio ranks. We find strong evidence that analysts also fail to understand the inefficiency in market prices. The forecasts errors are positively correlated with portfolio ranks for each combination of earnings forecast horizon and estimation method. For the hedged portfolio that is long in portfolio 5 and short in portfolio 1, the mean forecast errors are positive in all four cases and only insignificant for OLS based EPS2 forecasts, suggesting higher noise levels. This result is consistent with prior findings by Abarbanell and Bernard [1992] and Bradshaw et al [2001].

(Insert Table 8 about here)

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. The results based on OLS and LAD are quite similar. 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 and estimation method combinations. This result suggests that the stock market largely understands inefficiencies present in analysts' earnings forecasts. 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.

If the stock market understands the inefficiencies in analysts' forecasts, then, when one regresses abnormal stock returns on contemporaneous earnings surprises, one should obtain higher response coefficients and R^2 values if the forecasts are closer to the markets true expectations. In Table 9, we report such ERC regressions at the annual window. Our conjecture is confirmed. While for unadjusted earnings forecasts, the mean (median) earnings response coefficients for 12 annual regressions is 1.774 (2.097), and the mean (median) R^2 value is 0.079 (0.081); the estimates for LAD adjusted earnings forecasts are higher, with mean (median) coefficient value of 2.136 (2.342) and mean (median) R^2 value of 0.086 (0.098). Results for OLS adjusted forecasts are not better than the unadjusted forecasts, consistent with the fact that OLS overall does not improve forecasts out of sample.

(Insert Table 9 about here)

Combined with the finding that the market seems to understand inefficiencies present in analysts' forecasts, our results suggest that the stock market is overall more efficient than financial analysts. This conclusion is consistent with Liu [2004] who finds

that the market is more efficient in the reaction to quarterly earnings announcement than financial analysts.

5. Conclusion

In out-of-sample prediction tests, we find evidence that analysts' earnings forecasts do not efficiently impound publicly available information. Although both OLS and LAD generate significant in-sample results, LAD performs more consistently in out-of-sample tests. Our results confirm the advantages of using robust techniques for out-of-sample prediction, and suggest that analysts' inefficiency is present under an alternative loss function that minimizes the sum of absolute errors. Consistent with Easterwood and Nutt (1999), we find analysts' inefficiency primarily resides in forecasts that are predicted to be too optimistic. These stocks tend to be smaller in size and covered thinly by analysts.

The fact that we find both analysts and the market do not react efficiently to a common set of public information variables raises an interesting prospect that the two inefficiencies may be related. We find that when the market fails to understand certain public information, analysts do no better. However, the market seems to understand inefficiency in analysts' forecasts: a trading strategy based on predicted analyst earnings forecast errors does not generate abnormal profits. In addition, when we compare regressions of abnormal returns on contemporaneous earnings forecast errors based on analysts' original forecasts and forecasts adjusted by our prediction model, the latter regressions (based on LAD) have higher response coefficients and R^2 values. Combining

the evidence, we conclude that our results are consistent with the notion that the market is in general more efficient than analysts in processing public information.

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TABLE 1
Descriptive Characteristics of Sample Variables

The sample contains 15,409 firm-year observations between 1984 and 2000, representing all firms in *I/B/E/S* 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							
<i>Variable</i>	<i>Mean</i>	<i>Standard Deviation</i>	<i>1st Percentile</i>	<i>25th Percentile</i>	<i>Median</i>	<i>75th Percentile</i>	<i>99th Percentile</i>
<i>Error</i>	-0.024	0.507	-0.305	-0.021	-0.003	0.003	0.072
<i>Fret</i>	0.024	0.609	-0.911	-0.264	-0.040	0.199	1.955
<i>MV</i>	3,859	14,295	25	270	833	2,554	57,507
<i>Cover</i>	19.641	13.711	2.000	9.000	16.000	28.000	61.000
<i>Acc</i>	-0.035	0.077	-0.229	-0.071	-0.039	-0.003	0.193
<i>B/P</i>	0.515	0.480	-0.130	0.286	0.459	0.680	1.806
<i>E/P</i>	0.083	0.063	-0.023	0.063	0.081	0.101	0.201
<i>Ltg</i>	0.148	0.077	0.023	0.100	0.140	0.185	0.400
<i>Ltsg</i>	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
<i>UE</i>	-0.006	0.115	-0.113	-0.002	0.000	0.001	0.021
<i>Ret</i>	0.198	0.594	-0.655	-0.095	0.122	0.363	2.158
<i>Rev</i>	-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.

	<i>Error</i>	<i>Fret</i>	<i>MV</i>	<i>Cover</i>	<i>Acc</i>	<i>B/P</i>	<i>E/P</i>	<i>Ltg</i>	<i>Ltsg</i>	Δ PE	Δ OLA	<i>UE</i>	<i>Ret</i>	<i>Rev</i>
<i>Error</i>		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
<i>Fret</i>	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
<i>MV</i>	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
<i>Cover</i>	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
<i>Acc</i>	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
<i>B/P</i>	-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
<i>E/P</i>	-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
<i>Ltg</i>	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
<i>Ltsg</i>	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
Δ PE	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
Δ OLA	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
<i>UE</i>	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
<i>Ret</i>	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
<i>Rev</i>	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 Regressions of Analyst Forecast Errors on Prediction Variables*

The dependent variable is consensus (median) analyst forecast error for the upcoming annual earnings. 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 (Δ *PE* and Δ *OLA*), 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.

<i>Intercept</i>	<i>Acc</i>	<i>B/P</i>	<i>E/P</i>	<i>Ltg</i>	<i>Ltsg</i>	Δ <i>PE</i>	Δ <i>OLA</i>	<i>UE</i>	<i>Ret</i>	<i>Rev</i>	<i>R-square</i>
Panel A: OLS Regressions of Error on the Information Variables											
-0.020 (-4.56)	0.113 (2.11)										0.0003
0.267 (23.08)		0.010 (1.26)	-2.994 (-48.09)	-0.323 (-5.49)	-0.044 (-1.78)	0.215 (4.72)	-0.020 (-0.47)				0.1325
0.007 (2.46)								2.984 (118.60)	-0.019 (-4.20)	2.284 (30.26)	0.5608
0.149 (17.69)	-0.144 (-4.12)	0.001 (0.16)	-1.481 (-33.18)	-0.128 (-3.14)	-0.003 (-0.19)	-0.046 (-1.48)	-0.057 (-1.99)	2.828 (113.94)	-0.033 (-7.08)	2.049 (27.90)	0.5922
Panel B: LAD Regressions of Error on the Prediction Variables											
-0.004 (-25.24)	-0.016 (-8.59)										
0.017 (43.70)		-0.0148 (-54.00)	-0.115 (-55.68)	-0.043 (-21.84)	0.001 (0.67)	-0.004 (-2.70)	-0.001 (-0.57)				
-0.004 (-29.05)								0.446 (395.40)	0.005 (22.08)	0.720 (212.3)	
0.013 (34.40)	-0.010 (-6.26)	-0.009 (-36.20)	-0.098 (-49.30)	-0.041 (-22.10)	-0.000 (-0.07)	-0.009 (-6.04)	-0.001 (-0.44)	0.416 (371.3)	0.003 (15.92)	0.662 (199.7)	

TABLE 3*In-sample Pooled Regressions of Analyst Forecast Errors on Prediction Variables: Horizon Effects*

The dependent variable is consensus (median) analyst forecast error for the upcoming annual earnings. 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 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. Variables in Panel A, B and C are measured at one month after the release of the current fiscal year earnings, one month after the earnings release of the second fiscal quarter and one month before the release of the upcoming annual earnings. T-statistics are reported underneath coefficient estimates.

	<i>Intercept</i>	<i>Acc</i>	<i>B/P</i>	<i>E/P</i>	<i>Ltg</i>	<i>Ltsg</i>	ΔPPE	ΔOLA	<i>UE</i>	<i>Ret</i>	<i>Rev</i>
Panel A: Annual horizon											
OLS	0.223	-0.108	-0.005	-2.093	-0.236	-0.013	-0.055	-0.064	3.060	-0.040	2.011
	(22.35)	(-2.48)	(-0.73)	(-38.37)	(-4.93)	(-0.66)	(-1.53)	(-1.88)	(110.34)	(-7.20)	(24.92)
LAD	0.013	-0.011	-0.008	-0.104	-0.041	0.000	-0.009	0.001	0.446	0.003	0.701
	(31.01)	(-6.04)	(-29.38)	(-46.00)	(-20.76)	(-0.03)	(-5.86)	(0.83)	(387.97)	(14.09)	(209.62)
Panel B: Half year horizon											
OLS	0.164	-0.055	0.007	-1.584	-0.168	-0.003	-0.038	-0.064	2.752	-0.024	0.989
	(16.94)	(-1.31)	(1.06)	(-29.48)	(-3.62)	(-0.18)	(-1.09)	(-1.94)	(107.27)	(-3.84)	(20.11)
LAD	0.003	-0.001	-0.002	-0.025	-0.011	0.001	-0.002	0.000	0.168	0.001	0.466
	(15.93)	(-1.14)	(-19.13)	(-23.48)	(-12.08)	(3.29)	(-2.31)	(0.22)	(337.87)	(11.47)	(487.97)
Panel C: One month horizon											
OLS	0.136	-0.051	0.006	-1.221	-0.151	-0.005	-0.023	-0.060	2.007	0.018	3.256
	(16.44)	(-1.42)	(1.16)	(-26.67)	(-3.81)	(-0.29)	(-0.76)	(-2.14)	(79.77)	(3.49)	(40.81)
LAD	0.001	0.000	0.000	-0.004	-0.001	0.000	0.000	0.000	0.065	0.001	0.141
	(6.89)	(-1.00)	(3.82)	(-8.96)	(-2.91)	(0.26)	(-0.83)	(0.12)	(276.46)	(10.72)	(188.90)

TABLE 4
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 to the current values of the prediction variables to predict the forecast errors. Definitions: *MSE* is Mean Squared Error, *MAD* is Mean Absolute Deviation, *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.

<i>Year</i>	<i>N</i>	<i>Mean</i>	<i>Median</i>	<i>Std. Dev.</i>	<i>Std. Dev. Reduction</i>	<i>MSE</i>	<i>MSE Reduction</i>	<i>MAD</i>	<i>MAD Reduction</i>
Panel A: Distribution and Precision of Actual 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 and Precision of OLS Adjusted Analyst Forecast Errors									
1989	766	-0.0103	-0.0211	0.1786	-165.86	0.0319	-520.65	0.0984	-208.23
1990	807	0.0002	-0.0338	0.3047	-162.94	0.0927	-549.37	0.1142	-204.67
1991	951	-0.0066	0.0056	0.1488	-23.81	0.0222	-48.64	0.0330	-13.88
1992	986	0.0037	0.0137	0.0524	7.32	0.0028	20.95	0.0264	-11.02
1993	1,057	0.0059	0.0114	0.0522	-0.05	0.0028	2.94	0.0255	-22.89
1994	1,037	0.0066	0.0108	0.0641	10.58	0.0041	21.52	0.0265	-9.17
1995	1,066	-0.0015	0.0027	0.0436	13.33	0.0019	29.88	0.0213	4.90
1996	1,106	0.0032	0.0044	0.0466	4.75	0.0022	12.52	0.0214	-13.37
1997	1,162	-0.0096	-0.0037	0.0726	26.07	0.0054	46.16	0.0213	8.79
1998	1,174	0.0001	0.0039	0.0943	-30.74	0.0089	-63.75	0.0356	-12.80
1999	1,132	0.0010	0.0038	0.0796	2.00	0.0063	6.71	0.0346	-5.74
2000	1,097	-0.0177	-0.0034	0.1113	39.28	0.0127	63.73	0.0328	21.93
Mean		-0.0021	-0.0005	0.1041	-22.70	0.0162	-78.97	0.0409	-45.20
Panel C: Distribution and Precision 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 5
The stability of conditional coefficients: LAD vs. OLS

We first estimate the coefficients on the prediction variables in the same way as in Table 4 using past data. We then estimate the coefficients using each year's contemporaneous data. Finally, we take the difference between these two vectors of coefficient estimates and present the LAD result in Panel A and OLS result in Panel B.

<i>Year</i>	<i>Intercept</i>	<i>ACC</i>	<i>B/P</i>	<i>E/P</i>	<i>LTG</i>	<i>LTSG</i>	<i>PPE</i>	<i>OLA</i>	<i>UE</i>	<i>Ret</i>	<i>Rev</i>
Panel A: Out-of-sample Forecasts- In-sample fit for LAD.											
1989	0.0075	0.0000	-0.0054	0.0421	-0.0357	0.0000	0.0000	0.0000	0.1283	0.0023	-0.6235
1990	0.0011	0.0000	-0.0153	0.1187	0.0043	0.0000	0.0000	0.0000	-0.0402	-0.0044	-0.0308
1991	0.0063	0.0144	-0.0071	0.0260	-0.0298	0.0000	0.0000	0.0000	0.1471	0.0052	-1.0434
1992	0.0040	-0.0004	0.0052	-0.0197	-0.0225	0.0000	0.0000	0.0000	-0.0584	-0.0039	-0.2974
1993	0.0040	-0.0056	0.0000	-0.0809	-0.0091	0.0000	0.0000	0.0000	-0.0165	0.0003	0.3098
1994	0.0054	-0.0057	-0.0004	-0.0766	-0.0066	0.0000	-0.0019	0.0000	-0.9358	-0.0045	0.3256
1995	0.0008	0.0180	-0.0074	0.0310	-0.0031	0.0000	-0.0035	0.0000	-0.3746	0.0022	-0.1025
1996	0.0078	-0.0109	-0.0024	-0.0751	-0.0159	0.0000	0.0024	0.0000	-0.9303	-0.0012	0.6795
1997	0.0069	-0.0102	0.0091	-0.0858	-0.0012	0.0000	-0.0017	0.0000	-0.0848	-0.0004	0.1715
1998	-0.0061	-0.0187	0.0050	0.0627	0.0067	0.0000	0.0151	0.0000	0.4464	0.0036	-0.0984
1999	-0.0047	-0.0057	-0.0017	0.0716	0.0015	0.0000	-0.0089	0.0000	0.1301	0.0032	0.1785
2000	-0.0018	0.0078	0.0001	0.1009	0.0082	0.0000	0.0050	0.0000	-0.4281	-0.0020	-0.6909
σ_{lad}	0.0048	0.0106	0.0066	0.0747	0.0145	0.0000	0.0057	0.0000	0.4256	0.0033	0.4922
Panel B: Out-of-sample Forecasts- In-sample fit for OLS.											
1989	0.0536	0.0000	0.0000	-0.5766	0.0000	0.0000	0.0000	0.0000	0.4230	0.0000	-0.2610
1990	-0.0070	0.0000	0.0000	0.0000	0.0000	0.0000	0.1356	0.0000	0.0368	0.0081	-0.6199
1991	-0.0324	0.0000	0.0016	0.1862	0.0000	0.0000	0.1008	0.0000	0.2335	0.0354	-1.5182
1992	-0.0411	0.0000	0.0621	0.1124	0.0000	0.0000	0.0000	0.0000	-0.4994	0.0051	0.0045
1993	0.0003	0.0000	0.0000	-0.0880	0.0000	0.0000	0.0335	0.0000	-0.1929	0.0063	0.9380
1994	-0.0090	0.0000	0.0660	-0.4200	0.0533	0.0000	0.0000	0.0000	-0.8479	-0.0042	1.2767
1995	-0.0020	0.0000	0.0042	-0.1436	0.0513	0.0000	0.0000	0.0000	-1.0523	0.0053	0.0931
1996	0.0191	0.0000	-0.0026	-0.1928	-0.0145	-0.011	0.0000	0.0000	-1.4383	-0.0049	1.0264
1997	0.0216	-0.0038	0.0061	-0.2618	0.0040	0.0000	0.0000	0.0000	0.3296	0.0046	-0.0151
1998	0.0038	-0.0270	0.0095	-0.0951	0.0183	0.0000	0.0000	0.0000	1.1447	-0.0043	-0.6281
1999	-0.0088	-0.0127	0.0196	0.0000	0.0036	0.0000	0.0000	0.0000	0.8999	0.0072	0.6737
2000	0.0054	0.0562	-0.0246	0.1677	-0.0112	0.0000	0.0000	0.0000	-0.3914	0.0004	-2.9243
σ_{ols}	0.0247	0.0192	0.0264	0.2304	0.0219	0.0032	0.0463	0.0000	0.7773	0.0107	1.1837
$\sigma_{ols}-\sigma_{lad}$	0.0199	0.0086	0.0199	0.1557	0.0074	0.0032	0.0407	0.0000	0.3517	0.0074	0.6915

TABLE 6
The Sources of Improvement

Panel A reports the distribution of forecast errors of decile portfolios sorted by the forecasted forecast errors. *Improvement* is calculated as (MSE of adjusted forecast/MSE of actual forecast -1) *100. *% Improved* is the frequency in which OLS or 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 (Δ *PPE* and Δ *OLA*), 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.

	By OLS						By LAD					
	Mean adj Error	Med. Adj. Error	Mean Error	Med. Error	Improve- ment	% Improved	Mean Adj Error	Med. Adj. Error	Mean Error	Med. Error	Improve- ment	% Improved
1	-0.132	-0.049	-0.085	-0.038	-78.10	50.30	-0.049	-0.031	-0.092	-0.047	15.60	67.30
2	-0.045	-0.032	-0.032	-0.017	-1.50	46.90	-0.016	-0.016	-0.035	-0.022	13.50	67.10
3	-0.029	-0.025	-0.021	-0.011	12.30	47.70	-0.010	-0.011	-0.023	-0.012	9.10	63.10
4	-0.019	-0.018	-0.015	-0.006	11.50	44.10	-0.007	-0.008	-0.015	-0.006	6.30	57.90
5	-0.011	-0.013	-0.009	-0.003	-1.40	35.80	-0.005	-0.005	-0.008	-0.003	4.40	55.50
6	-0.005	-0.008	-0.006	-0.001	-21.60	31.10	-0.003	-0.004	-0.006	-0.001	1.30	52.40
7	0.001	-0.004	-0.006	-0.001	-67.30	32.30	-0.002	-0.002	-0.005	-0.001	0.50	50.20
8	0.008	-0.001	-0.004	0.000	-101.20	32.20	0.000	0.000	-0.002	0.000	-0.60	49.30
9	0.016	0.003	-0.003	0.001	-211.00	29.00	0.002	0.002	0.000	0.000	-2.30	44.40
10	0.049	0.011	-0.008	0.001	-145.40	24.10	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.

	<i>MV</i>	<i>Cover</i>	<i>Acc</i>	<i>BP</i>	<i>EP</i>	<i>Ltg</i>	<i>Ltsg</i>	Δ <i>PPE</i>	Δ <i>OLA</i>	<i>UE</i>	<i>Ret</i>	<i>Rev</i>
<i>By OLS</i>												
1	643	12.9	-0.039	0.859	0.130	0.17	0.18	0.033	0.021	-0.035	-0.197	-0.025
2	1,100	14.8	-0.025	0.677	0.106	0.16	0.17	0.041	0.029	-0.003	-0.065	-0.006
3	1,891	16.8	-0.029	0.599	0.096	0.15	0.16	0.043	0.035	-0.001	0.017	-0.004
4	2,323	18.3	-0.030	0.527	0.087	0.15	0.15	0.039	0.031	0.000	0.066	-0.002
5	3,102	19.5	-0.033	0.489	0.081	0.14	0.14	0.037	0.034	-0.001	0.124	-0.001
6	3,753	19.5	-0.033	0.452	0.076	0.14	0.14	0.038	0.035	0.000	0.205	-0.001
7	4,867	20.2	-0.035	0.402	0.072	0.14	0.13	0.038	0.032	0.000	0.233	-0.001
8	6,382	21.3	-0.041	0.378	0.066	0.14	0.14	0.033	0.038	0.000	0.335	0.000
9	9,071	22.3	-0.043	0.335	0.060	0.15	0.14	0.033	0.036	0.001	0.452	0.000
10	8,044	19.7	-0.051	0.314	0.036	0.17	0.17	0.031	0.038	0.001	0.857	-0.002
<i>By LAD</i>												
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 7
Out-of-sample Forecast of 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 to the current values of the prediction variables to predict the abnormal returns of the current year. We form five quintile portfolios based on the predicted return values. From portfolio 1 to portfolio 5, the predicted returns increase.

<i>Year</i>	<i>OLS</i>						<i>LAD</i>					
	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>(5-1)</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>5</i>	<i>(5-1)</i>
1989	0.042	-0.020	-0.013	0.052	0.116	0.074	0.041	-0.041	-0.010	0.048	0.139	0.098
1990	0.004	-0.005	-0.033	-0.056	0.044	0.040	-0.011	-0.017	-0.051	0.015	0.018	0.029
1991	-0.107	0.015	0.062	0.057	0.026	0.134	0.022	0.009	0.026	-0.010	0.007	-0.015
1992	-0.048	0.053	-0.004	0.058	0.109	0.157	-0.057	0.026	0.003	0.056	0.141	0.198
1993	-0.079	0.000	0.040	0.010	0.040	0.119	-0.088	-0.001	0.008	0.034	0.057	0.145
1994	-0.082	-0.086	-0.017	-0.010	0.021	0.103	-0.092	-0.086	-0.042	-0.035	0.082	0.174
1995	-0.130	0.021	-0.005	-0.048	0.006	0.136	-0.101	-0.036	0.013	-0.021	-0.012	0.089
1996	-0.118	-0.053	-0.040	0.001	0.051	0.169	-0.090	-0.077	-0.020	-0.026	0.054	0.144
1997	-0.185	-0.116	-0.092	-0.078	-0.041	0.144	-0.195	-0.131	-0.061	-0.074	-0.052	0.143
1998	-0.028	0.036	-0.139	-0.127	0.275	0.302	0.037	0.066	-0.173	-0.144	0.231	0.195
1999	0.304	0.380	0.343	0.307	0.169	-0.135	0.223	0.335	0.374	0.293	0.278	0.055
2000	-0.027	0.102	0.169	0.261	0.228	0.255	0.203	0.186	0.166	0.151	0.027	-0.176
Average	-0.038	0.027	0.023	0.035	0.087	0.125	-0.009	0.019	0.020	0.024	0.081	0.090

TABLE 8*The Relationship between Forecasted Abnormal Returns and Forecasted Forecast Errors*

In Panel A, we form decile portfolios based on predicted abnormal returns. *Error1* is actual analyst forecast error for the upcoming annual earnings, and *Error2* is actual 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

<i>By OLS</i>					<i>By LAD</i>				
<i>Rank</i>	<i>Error1</i>	<i>T-Stat</i>	<i>Error2</i>	<i>T-Stat</i>	<i>Rank</i>	<i>Error1</i>	<i>T-Stat</i>	<i>Error2</i>	<i>T-Stat</i>
1	-0.033	-8.092	-0.051	-9.089	1	-0.039	-9.524	-0.057	-8.293
2	-0.019	-6.908	-0.033	-7.396	2	-0.020	-11.093	-0.034	-8.435
3	-0.012	-7.437	-0.023	-9.056	3	-0.013	-5.469	-0.023	-7.263
4	-0.011	-5.584	-0.022	-7.334	4	-0.009	-3.130	-0.020	-4.926
5	-0.018	-3.769	-0.024	-6.611	5	-0.012	-2.273	-0.019	-5.295
5-1	0.015	2.441	0.027	0.026	5-1	0.027	3.792	0.038	5.020

Panel B: Portfolios sorted on predicted analyst forecast errors

<i>By OLS</i>					<i>By LAD</i>				
<i>Rank</i>	<i>Fret4</i>	<i>T-Stat</i>	<i>Fret13</i>	<i>T-Stat</i>	<i>Rank</i>	<i>Fret4</i>	<i>T-Stat</i>	<i>Fret13</i>	<i>T-Stat</i>
1	0.016	1.656	0.030	0.770	1	0.021	1.542	0.039	0.989
2	0.017	1.549	0.016	0.385	2	0.015	1.350	0.004	0.085
3	0.026	1.932	0.032	0.820	3	0.022	2.454	0.015	0.519
4	0.018	2.431	0.012	0.471	4	0.020	1.947	0.018	0.563
5	0.037	2.400	0.045	1.391	5	0.035	2.838	0.059	2.662
5-1	0.021	1.593	0.014	0.305	5-1	0.014	1.046	0.020	0.667

TABLE 9*The Market Understanding of Inefficiency in Analyst Forecasts*

In each year, we first estimate the full model using data from the past five years, and then apply the estimated coefficients to the current values of the prediction variables to predict the forecast errors and adjust the raw analyst forecasts. We then regress the 13 month size adjusted abnormal returns on the contemporaneously measured earnings surprises. The first column reports the ERC regression results based on unadjusted analyst forecasts; the second column is based on OLS-adjusted forecasts; the third column is based on LAD-adjusted forecasts. T-statistics are reported under coefficient estimates.

	<i>Raw Forecast Errors</i>			<i>OLS-adjusted Forecast Errors</i>			<i>LAD-adjusted Forecast Errors</i>		
	<i>Intercept</i>	<i>ERC</i>	<i>R²</i>	<i>Intercept</i>	<i>ERC</i>	<i>R²</i>	<i>Intercept</i>	<i>ERC</i>	<i>R²</i>
1989	0.081 (5.06)	1.810 (8.11)	0.079	0.037 (2.40)	0.214 (2.46)	0.008	0.069 (4.49)	2.186 (8.92)	0.094
1990	0.024 (1.50)	1.133 (8.41)	0.081	-0.009 (-0.57)	0.186 (3.51)	0.015	0.012 (0.79)	1.331 (9.55)	0.102
1991	0.026 (2.01)	0.704 (6.62)	0.044	0.014 (1.08)	0.481 (5.57)	0.032	0.024 (1.89)	1.021 (7.53)	0.056
1992	0.063 (4.76)	1.692 (7.50)	0.054	0.028 (2.17)	1.821 (7.48)	0.054	0.052 (4.04)	1.911 (7.78)	0.058
1993	0.029 (2.94)	2.421 (13.12)	0.140	-0.012 (-1.26)	2.449 (13.31)	0.144	0.009 (0.89)	2.497 (13.38)	0.145
1994	-0.004 (-0.26)	2.383 (10.83)	0.102	-0.053 (-3.37)	2.946 (12.15)	0.125	-0.025 (-1.58)	2.851 (11.98)	0.122
1995	0.005 (0.41)	2.642 (11.72)	0.115	-0.026 (-2.32)	3.500 (13.74)	0.151	-0.007 (-0.64)	3.269 (13.03)	0.138
1996	-0.001 (-0.08)	3.054 (11.13)	0.101	-0.043 (-3.23)	3.490 (12.25)	0.120	-0.020 (-1.51)	3.467 (12.13)	0.118
1997	-0.089 (-6.48)	0.749 (5.44)	0.025	-0.092 (-6.73)	1.136 (6.12)	0.031	-0.089 (-6.50)	0.962 (5.88)	0.029
1998	0.044 (1.05)	2.806 (4.76)	0.019	-0.001 (-0.03)	2.470 (4.33)	0.016	0.025 (0.60)	3.563 (6.07)	0.031
1999	0.343 (16.03)	3.073 (11.83)	0.110	0.295 (14.23)	3.616 (13.60)	0.141	0.327 (15.53)	3.413 (12.74)	0.126
2000	0.106 (5.26)	-1.175 (-9.83)	0.081	0.131 (6.38)	-0.978 (-4.68)	0.020	0.127 (6.01)	-0.838 (-3.71)	0.012
Mean	0.052	1.774	0.079	0.022	1.778	0.071	0.042	2.136	0.086
Median	0.028	2.097	0.081	-0.005	2.135	0.043	0.018	2.342	0.098