

# Investment Analysts' Forecasts of Earnings\*

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## Abstract

Much of the analysis of forecasts of firms' earnings by investment analysts focuses on the deviation between mean earnings and the mean forecasts of those earnings. Most researchers assume the existence of a predictable difference (forecast bias) between the two measures and are more focused on understanding the dynamics of the forecasting behavior and associated incentives for such biases (Clarke and Subramanian, 2006; Boni and Womack, 2002, Frankel, Kotari, and Weber, 2006). Others are cautious about accepting such forecast biasness automatically and question the appropriateness of statistical methods and properties used to determine the differences (Keane and Runkle, 1990, 1998). Our paper attempts to provide additional and comprehensive evidence on the distribution of analysts' forecasts for all U.S. firms by analyzing the entire period from 1990 to 2004 as well as for individual years and industries. The evidence indicates a substantial asymmetry of earnings, earning forecasts and forecast errors. We find strong support for average and median earning forecasts being higher than actual earnings a year before the earnings announcement. Such differences between earnings and forecasts also exist across time periods and industries. A month before the earnings announcement, mean and median forecast errors are small.

*Keywords:* Analysts' forecasts - Earnings forecasts - Biased forecasts

*Jel Numbers:* G17, C53.

## INTRODUCTION

Do stock analysts provide information on stocks, or are they merely salespeople issuing one-sided information about stocks? In addition to forecasting earnings which are used by some investors when they buy firms' stocks, analysts at investment banks often have participated in other activities such as convincing the same firms to use the investment bank to issue stock. These activities were the basis of suits by the New York Attorney General against major investment banks. Rather than going to trial, the charges were settled in April 2003. In the resulting settlement, investment banks agreed to substantial changes in their businesses designed to provide less incentive for analysts to be influenced by the investment banks' activities. The investment banks also agreed to make payments totalling \$1.4 billion. This \$1.4 billion covered fines, payments to investors, funding of investor education and funding of research by independent analysts. This settlement brings into question the informativeness of analysts' projections of earnings, suggesting that analysts' projections of earnings largely or substantially reflect analysts' interests rather than an assessment of a firm's prospects.

On the other hand, charges of an insider trading scheme in 2007 suggest that analysts' forecasts do contain information and affect prices. This scheme involved an accomplice receiving advance information about analysts' forecasts and taking positions in advance of the announcements (Smith, Scannell and Davies, 2007). This scheme makes no sense if analysts' forecasts are uninformative and ignored. While indicating that at least some analysts' forecasts may be informative, such activities do not imply that forecasts are the best possible. It is possible to take imperfect information and filter it for any predictable misinformation.

Are there predictable differences between analysts' earnings forecasts and actual earnings? Many papers show that the analysts' forecast errors are predictably different

than actual earnings.<sup>1</sup> The evidence indicates that analysts' forecasts of earnings well before the announcement are higher on average than actual earnings. Whatever earnings an analyst forecasts for a firm, a better prediction is a somewhat lower level of earnings. This predictable difference is called a "bias" in the forecasts.<sup>2</sup> Some papers also suggest that analysts' forecasts close to the earnings announcement decline to become less than actual earnings. The rationale for this reversed bias is a suggestion that earnings greater than recent forecasts are interpreted as a positive earnings surprise and the firms' stock prices increase.

The purpose of this paper is to provide an overview of analysts' forecasts and the forecasts' relationship to actual earnings. Our data are for U.S. analysts' forecasts of U.S. firm's earnings from 1990 through 2004. These data show the usual result that analysts' forecasts are greater than earnings on average. We look at the distribution in more detail and find that the distribution of earnings is asymmetric. The distribution of earnings forecasts also is asymmetric but not sufficiently asymmetric that forecast errors are symmetric; earnings forecast errors also are asymmetric. We also find that median forecasts are closer to actual forecasts than are mean forecasts. We examine differences between actual earnings and earnings forecasts over time and by industry. We find substantial differences in forecast accuracy across industries and larger forecast errors in recessions. Forecast errors at the one-month horizon are small.

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<sup>1</sup>Sirri (2004) summarizes a few of these papers and provides references.

<sup>2</sup>Not all research agrees that analysts' forecasts are biased. Keane and Runkle (1990, 1998) suggest that the statistical results are affected by two errors and one aspect of the data. First, many old tests use average survey data instead of individual data. The finding of bias survives this criticism. Second, many results overstate the statistical significance of test results because the tests ignore correlation within analysts' forecast in the same industry in a given year and discretionary asset write-downs. Finally, asset write-downs can generate forecast errors that appear to be predictable in the data after the fact if the timing and magnitudes of write-downs are uncertain.

## ERRORS IN FORECASTING EARNINGS PER SHARE

### Data

Analysts forecast companies' earnings per share, and the forecast error is the difference between actual earnings and these forecasts of earnings. There is a scale problem with using the level of forecasts across firms and over time. For example, suppose that a firm has a forecast error of \$1 in earnings with actual earnings per share of \$10 and a stock price of \$100. If the firm had twice as many shares outstanding, everything else the same, the firm would have a forecast error of \$.50 with actual earnings of \$5 and a stock price of \$50. Another way of seeing the problem is to note that a \$1 error in forecasting earnings is very different if actual earnings are \$10 than if they are \$5. One way to adjust for differences in the magnitude of earnings per share and forecast errors across firms is to divide the forecast error by the stock price. Dividing by the stock price assumes that errors in forecasting earnings per share relative to the stock price are relatively homogeneous across firms. Earnings per share relative to the stock price is the inverse of the price-earnings ratio, often used as part of the information used to evaluate companies.<sup>3</sup>

The forecast error relative to the stock price is

$$e_{T,t}^{i,j} = \frac{a_T^i - f_{T,t}^{i,j}}{p_{T-1}^i}, \quad (1)$$

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<sup>3</sup>Another way to scale earnings per share would be to divide by the level of earnings to get the proportional error in forecasting earnings. Earnings close to zero and negative earnings create serious problems for this normalization. Dividing by earnings can generate a very large relative forecast error as earnings go to zero; dividing by negative earnings would change the sign of the forecast error. Stock prices cannot be zero and are strictly positive. While prices can approach zero, earnings generally approach zero at a related rate, which is another way of saying that earnings per share relative to the stock price is relatively homogeneous across firms.

where  $e_{T,t}^{i,j}$  is the computed relative forecast error for company  $i$  by analyst  $j$  for year  $T$  made  $t$  months before the release date,  $a_T^i$  is actual earnings per share of company  $i$  in year  $T$ ,  $f_{T,t}^{i,j}$  is the forecasted earnings per share for company  $i$  by analyst  $j$  made for year  $T$  with the forecast being made  $t$  months before the release date and  $p_{T-1}^i$  is the stock price for company  $i$  at the end of the previous year  $T - 1$ .

The forecast horizon,  $t$ , is calculated as the difference in months between the estimation date (I/B/E/S variable ESTDATX) and the report date (I/B/E/S variable REPDATX). We use the report date (REPDATX) instead of forecast period end date (FPEDATX) because analysts can make forecasts between the fiscal year's end and the date earnings are reported.

The data on forecasts of earnings per share and actual earnings per share are from the I/B/E/S Detail History with Actuals database for 1990 through 2004. Any company with at least one forecast between 1990 and 2004 is included in the initial database.

Stock prices are from the CRSP database from 1989 to 2003. The earnings in any year are divided by the stock price at the end of trading in the prior year. With this choice of stock price, the stock price does not reflect the changes in forecasts or the ensuing forecast errors made during the year.

The initial number of observations on forecasts is 1,835,642. To avoid non-synchronized timing of forecasts by year, we restrict the analysis to companies with fiscal years ending in December.<sup>4</sup> This reduces the number of observations to 1,207,445. We restrict our analysis to forecasts by analysts located within the United States, which reduces the number of observations to 678,427 forecasts for 6,731 companies. In this paper, a company's stock is defined by 6-digit CUSIP (Committee on Uniform Securities Iden-

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<sup>4</sup>When looking at data by year, having the same end date means that the same events are occurring at the same horizon for all firms. Firms with fiscal years ending in December are about 74 percent of all firms in the I/B/E/S database.

tification Procedures) number followed by an “01” which indicates a common stock.<sup>5</sup> We match U.S. companies from I/B/E/S and CRSP by CUSIP. We also associate an Industry Code according to the Global Industries Classification Standard from Standard and Poor’s.

Finally, to eliminate possible transcription errors, we cut off the distributions of both actual and forecasted earnings per share relative to the stock price at the first and ninety-ninth percentile for each year and forecast horizon. This results in a dataset with 662,016 observations for 6,574 companies. The number of firms included in the analysis increases over time. The number of U.S. companies with a fiscal year ending in December and an earnings’ forecast by at least one U.S. analyst increases from 1,446 in 1990 to 2,569 in 2004.<sup>6</sup> The analyses by industry use the industry classification, which is not available for 104,840 observations. As a result, the analyses by industry use 557,176 observations instead of the whole sample of 662,016 observations.

### **Distribution of Forecast Errors**

Figure 1 shows the distributions of earnings and forecasted earnings. The graphs show the distribution of actual earnings and the distribution of forecasts by analysts made one month, six months and twelve months before the earnings announcement. For example, the first graph shows actual earnings per share relative to the stock price and forecasts made one month before the announcement of earnings. The second graph shows the distribution of earnings and the distribution of the forecasts made six months before the earnings announcement, and the third graph shows the distribution of earnings and the distribution of the forecasts made twelve months before the earnings announcement.<sup>7</sup> Deleting the top and bottom one percent of the

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<sup>5</sup>A CUSIP number followed by the two-digit security code identifies a particular security.

<sup>6</sup>Appendix Table 1 shows the number of companies in our analysis by year.

<sup>7</sup>The distribution of earnings is not the same at each of the horizons. The figure shows the distribution of all forecasts and the distribution of the actual earnings that were predicted. Every

distribution still leaves quite long tails to the distribution of earnings and to a lesser but still easily discernible extent, the forecasts. To avoid obscuring detail, we also truncate these figures at  $-\$0.50$  and  $+\$0.50$  per dollar of share price. Table 1 shows the distribution of earnings, forecasts and the forecast errors without the truncation. Relative to the total number of observations, the truncation excludes a small number of observations mostly in the negative tail of the distributions.

The forecasts and actual earnings are strikingly similar, which is consistent with the forecasts being quite informative about actual earnings. The histograms for forecasts and actual earnings are distinguishable, but the overlap far outweighs the differences. The dashed vertical lines are drawn at the mean of actual earnings. The most common – modal – values of forecasted and actual earnings are similar. The solid curves in the figure represent normal distributions with the same means and standard deviations as actual earnings. Actual and forecasted earnings have higher peaks at the mean value than the normal distribution and also have fatter tails. Because the total area must add up to one hundred percent, this implies that the distributions of actual and forecasted earnings have fewer observations between the tails and the center of the distribution.

The graph of the 12-month-ahead forecasts shows the bias in longer-term forecasts. While the distributions of actual and predicted earnings are quite similar, the histogram shows that there tend to be more forecasts of above average earnings and fewer forecasts of below average earnings than actual earnings. The distribution of the six-month-ahead forecasts shows less bias. The distribution of the one-month-ahead forecasts is more similar to the actual earnings.

The literature focuses on the deviations between the earnings and the forecasts, 

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firm with a forecast appears in the figure; every firm with no forecast does not appear in the figure. In addition, every firm with more than one forecast appears in the figure the same number of times as the number of forecasts.



which makes it easy to lose sight of how informative the forecasts are about actual earnings. Analysts' earnings forecasts are quite informative about actual earnings.

Figure 2 shows the distributions of the forecast errors. A positive forecast error means that actual earnings exceed the forecasted earnings. A negative forecast error means that actual earnings fall short of the forecasted earnings. If all analysts forecasted earnings within a penny of earnings per dollar of share price, all the forecast errors would be in the two bars surrounding zero. Recall that the share price is the price before the start of the fiscal year, so this indicates that the analysts are coming quite close to forecasting actual earnings. In fact, the forecast errors are quite peaked near zero, whether twelve months, six months or one month before the announcement of actual earnings.

The earnings forecasts are closer to actual earnings a month before the earnings announcement than twelve months before the earnings announcement. This convergence is to be expected if the forecasts are informed predictions. More information becomes available as time goes on, and this information is substantial. Eleven-twelfths of the year is past when the one-month-ahead forecast is made. Firms announce earnings quarterly; when the one-month-ahead forecast is made, earnings for the first three quarters of the year have been announced and are known. Besides this relatively mechanical effect as time passes, other information becomes known about earnings as time passes and the magnitudes of forecast errors can be expected to decrease.

The forecasts made one month before the earnings announcement are almost all within one penny of earnings per dollar of share price. Over 90 percent of the earnings are within a penny of actual earnings per dollar of share price. There is a clear asymmetry in the distribution of these close forecast errors. Sixty percent of the earnings are more than the forecasts and within a penny; thirty percent of the earnings are less than the forecasts and within a penny. The larger number of positive forecast errors can reflect analysts' forecasts that the analyst knows are too low; it also can occur for

other reasons. For example, firms with actual earnings less than forecasted earnings may provide analysts with information before the announcement and forecasts are revised accordingly.

The forecast errors twelve months ahead and six months ahead also show asymmetry, with many forecasts within a penny of actual earnings but more above zero than below.

Table 2 shows detailed information about the distributions of forecast errors by year at horizons of twelve months, six months and one month. The table shows the maximum and minimum values, the mean, standard deviation, measures of the skewness and kurtosis of the distribution of forecast errors and selected percentiles of the distributions.

As Figure 2 suggests, the forecasts a month before the earnings announcement are much closer to actual earnings than are forecasts a year in advance. The standard deviation of forecast errors is a measure of the size of analysts' errors, independent of whether the forecast is above or below actual earnings. The standard deviation is substantially larger twelve months before earnings are announced than one month before the earnings announcement. For example, in 1990, the standard deviation is 0.075 at a horizon of twelve months, 0.067 at a horizon of six months and 0.034 at a horizon of one month. In 2004, the standard deviation is 0.031 at a horizon of twelve months, 0.020 at a horizon of six months and 0.009 at a horizon of one month.

The mean forecast errors in the table also decline as the announcement of earnings for the year approaches. The largest magnitudes of mean forecast errors in the table are for the twelve-month horizon, -2.7 cents per dollar of share price in 1990 and 2001 and -2.5 cents per dollar of share price in 1991. The smallest magnitudes of mean forecast errors are for the one-month horizon. At the one month horizon, the mean forecast error farthest from zero is -0.35 cents per dollar of share price in 1990 and the mean forecast error has been hundredths of a penny per dollar of share price in

most of the years since.

There is a large literature that examines these mean forecast errors. The negative mean forecast errors are statistically significant and not trivial in magnitude at the twelve-month horizon. Twelve months before earnings are announced, analysts' forecasts on average are over-estimates of actual earnings. This over-estimation is predictable, in an interesting and specific sense. If all one knows about earnings forecasts a year in advance is the forecast, actual earnings will be less on average. The difference is not large, but it is not zero and it is predictable. If analysts are attempting to forecast earnings well on average, they are not as good as they could be. In standard parlance, the forecasts are biased: the average forecast error is not zero.

Besides the arithmetic average, the median is another measure of the typical forecast. The median is the middle forecast, the forecast which divides the forecasts into two parts, with half the observations above the median and half below the median. The median forecast error is noticeably closer to zero than the average forecast error. This indicates that the typical negative forecast error is larger in magnitude than the typical positive forecast error. In other words, as Figure 2 shows, the distribution of forecast errors is not symmetric. The percentiles of the distribution clearly show this asymmetry of forecast errors.

The consistently negative values of skewness in Table 2 also indicate what Figure 2 shows: negative forecast errors are larger in magnitude than the positive errors.<sup>8</sup> Consistent with the figures, the measure of skewness indicates that forecast errors are skewed toward negative values.<sup>9</sup>

Kurtosis measures how concentrated a distribution is around the mean compared

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<sup>8</sup>The measure of skewness is the third moment about the mean divided by the standard deviation cubed.

<sup>9</sup>Skewness is measured by the skewness coefficient, the third moment about the mean divided by the standard deviation cubed.

to how many observations are in the tails of the distribution.<sup>10</sup> The positive values for kurtosis indicate that the tails of the distribution have more observations than would be suggested by a normal distribution. Tests for normality of the distribution of forecast errors uniformly are inconsistent with a normal distribution.<sup>11</sup>

Figures 3 and 4 show aspects of the distributions of forecast errors for all horizons from 1990 to 2004. Figure 3 shows the mean and median forecast errors as the horizon – the length of time before the earnings announcement – goes to zero. It also shows the median in combination with the twenty-fifth and seventy-fifth percentiles of the distribution of forecast errors. The mean forecast errors are more negative than the medians at long horizons, and consequently show more convergence to zero. The median forecast errors are negative, with the largest magnitudes in 1990, 1991, 1998 and 2001. With the exception of 1998, these larger-magnitude median forecast errors are associated with recessions.<sup>12</sup> The mean forecast errors are more negative than the median forecast errors but decrease to be quite close to zero by one month before the earnings announcement.

Figure 4 shows the distribution of forecast errors by year by graphing the median forecast error and the twenty-fifth and seventy-fifth percentiles of the distribution for each horizon for each year from 1990 to 2004. The asymmetry of the distributions is quite apparent. It also is clear that actual earnings fall short of the longer horizon forecasts during recessions; this is indicated by the much more negative forecast

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<sup>10</sup>The specific measure of kurtosis in the table is the fourth moment about the mean minus three relative to the fourth power of the standard deviation.

<sup>11</sup>The test for normality is the Bera-Jarque test. The inconsistency with a normal distribution is consistent with the figures and tables; a normal distribution is symmetric and does not have the relative fat tails indicated by the kurtosis statistics. The Bera-Jarque test statistics are not included in the table because the p-values uniformly are inconsistent with a normal distribution with p-values of  $10^{-8}$  or below.

<sup>12</sup>The National Bureau of Economic Research dates the recession in 1990 and 1991 from July 1990 to March 1991 and the recession in 2001 from March 2001 to November 2001.

errors during the recession years 1990, 1991 and 2001. Given the unpredictability of recessions, this is not especially surprising. The figure suggests that the distribution has become more symmetric over time, although the occurrence of recessions clearly is associated with greater asymmetry.

Table 3 presents the results of tests whether the apparent skewness in the figures is statistically significant and consistent across horizons and years. The results of two tests are presented. The first is the sign test, which is a test whether the median equals the mean. If a series' median exceeds its mean, the value of the statistic is positive and the p-value indicates the probability of a deviation that large if there really were no deviation. The second test is a test whether the skewness coefficient is zero. If the skewness coefficient is zero and moments of the distribution up to the sixth are finite, then the skewness coefficient has an asymptotic normal distribution that can be used to construct a test.<sup>13</sup>

The sign tests indicate an asymmetry in forecast errors which persists from 1990 through 2004. Tests for the equality of the median and mean at all horizons are quite inconsistent with their being the same. At the twelve-month horizon, the median forecast error is closer to zero than the mean for all years from 1990 through 2004; all of the differences are statistically significant at any usual significance level. The difference is far smaller in 2004 than in earlier years but the difference still is statistically significant. The difference is one-tenth of a penny per dollar share price in 2004. Given a typical price-earnings ratio of 15 or 20, this implies a forecast error in earnings on the order of two cents per share per dollar of earnings twelve-months ahead. There is some suggestion that the difference between the mean and the median has been declining over time. The smallest deviations between the median and the mean

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<sup>13</sup>The mean of the asymptotic distribution of the skewness coefficient is zero under the null hypothesis and the variance is  $(\mu_6 - 6\sigma^2\mu_4 + 9\sigma^6) / T\mu_2^3$ , where  $\mu_n$  is the  $n$ th moment and  $\sigma$  is the standard deviation (Gupta 1967, pp. 850-51.)

occur in 2003 and 2004.

The tests using the skewness coefficient indicate that deviations from symmetry are persistent from 1990 through 2004 only at the twelve-month horizon. The null hypothesis of symmetry for the twelve-month horizon cannot be rejected in 2002 at the five percent significance level, a result most simply interpreted as being due to chance rather than anything special about 2002. There is less evidence of overall skewness in any year at the six-month horizon and there is scant evidence of asymmetry at the one-month horizon. This is an interesting contrast to the results using the median and mean. While there are statistically significant differences between the mean and median, the overall skewness of the distribution is less pronounced based on the third moment which summarizes the asymmetry of the distribution.<sup>14</sup>

### **Forecasts Error Across Industries**

Forecast errors across firms and analysts are likely to differ for a variety of reasons, one being the likelihood that earnings are more predictable for some industries than others.

Figure 5 shows forecast errors by two-digit Global Industry Classification System (GICS). Forecast errors vary substantially by industry. All of the figures have the same scale to make it easy to compare forecast errors across industries. Earnings in health care are predicted with relatively small forecast errors and earnings in energy firms are predicted particularly poorly. It is plausible that earnings forecasts in less volatile industries are smaller. Energy prices are subject to large unpredictable price swings, which obviously affect earnings. While health care prices have risen substantially in

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<sup>14</sup>Too many rejections of the null hypothesis are possible if data have high kurtosis (Premaratne and Bera 2005), as our do. This is only an issue at the twelve-month horizon since only that horizon shows rejections. Given the results for the median and mean and the levels of significance, we are inclined to take the rejections as being real rather than an artifact of kurtosis.

recent years, the increases have been relatively consistent and therefore predictable. Health care is virtually unaffected by recessions, while the demand for energy falls in recessions. Some other industries show low earnings around recessions as well, such as materials and consumer discretionary goods. If recessions are not predicted, there is little reason to think that these earnings decreases are predictable either.

Table 4 shows the p-values of sign tests for the industries by horizon. The data for all industries taken together are inconsistent with symmetry for all years for each of the three horizons: twelve months, six months and one month. At the twelve-month horizon, there is a clear distinction between telecommunications, utilities and the rest of the industries. For telecommunications and utilities, forty percent of the sign tests are consistent with equality of the mean and median. Still, even for these industries, most of the sign tests are inconsistent with symmetry. The six-month and one-month horizons are inconsistent with symmetry also. Overall, the sign tests are consistent with persistent differences between the median and means of the forecast errors but suggest variation in the asymmetry by industry.<sup>15</sup>

## UNBIASEDNESS OF EARNINGS FORECASTS

Almost all of the existing literature on analysts' forecasts examines whether analysts' forecasts are biased and, generally speaking, finds that analysts overestimate earnings. This overestimation falls as the earnings announcement approaches, as indicated in Table 2, but earnings in the future typically are noticeably less than the average forecast. There is some evidence and analysis suggesting that analysts' forecasts

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<sup>15</sup>The tests on skewness coefficients are not presented because they do not seem as informative to examine in detail. The evidence for asymmetry is much weaker with this test. Even at the twelve-month horizon, the evidence for skewness in individual industries is not nearly as strong as for all industries. There is not much evidence of overall asymmetry at the aggregate level and the results by industry provide no evidence of persistent asymmetry for any particular industry.

change from over-estimates to under-estimates just before the earnings announcement. Such near-term forecasts are supposed to be helpful to firms' managements because the announcement of higher than forecasted earnings generates favorable publicity and a higher stock price after the announcement.<sup>16</sup>

Forecasts not being too high or low on average seems like a relatively simple thing to ask, especially compared with asking that forecasts be accurate. Even so, it is possible that analysts process the information available to them as best as possible, but some or all analysts do not have an incentive to produce forecasts that are correct on average.

### **Analysts' Incentives and Forecasts**

At first glance, it seems obvious that unbiased forecasts are the best forecasts. A biased forecast is high or low on average. Such a bias suggests that the forecast can be improved by adjusting the forecast by the bias. There are many conditions in which an unbiased forecast is the best one. A common criterion for forecast errors is mean squared error. If a forecaster wants to minimize the expected mean squared error of a forecast, then an unbiased forecast is the best one.<sup>17</sup> The expected squared forecast error applies an increasing penalty to forecasts farther from the average – a forecast twice as far from zero is four times as bad.

The mean is not necessarily the best forecast in all general circumstances. Suppose that someone is trying to forecast the value shown when a fair die is thrown. The mean forecast is the average of 1, 2, 3, 4, 5 and 6, which is 3.5. If the forecaster's earnings depend on how close the forecast is to the actual value, the best forecast in fact is 3.5. On the other hand, if the forecaster gets paid only when the value shown is

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<sup>16</sup>We leave aside whether this line of argument is plausible.

<sup>17</sup>A minimum expected square error forecast minimizes  $Ee^2$ , where subscripts and superscripts have been suppressed for the error  $e$  for simplicity.



the same as the value forecasted, this unbiased forecast guarantees that the forecaster always loses. The die will never have the value 3.5. If the forecaster is paid when the forecast is the same as the value thrown and values from one to six are equally likely, any integer forecast from one to six is equally good and 3.5 never is predicted. While this is a simple example, the point is more general. The value forecasted depends on the forecaster's incentives and the distribution of the data. An unbiased forecast may not be the "best" forecast.

There also are objectives similar to minimizing expected squared error which lead to forecasts being "biased." If a forecaster wants to minimize the expected absolute deviation of the forecast error, then the median is the best forecast.<sup>18</sup> The absolute forecast error applies an increasing penalty to forecast errors farther from zero – a forecast error twice as far from zero is twice as bad. The cost of forecast errors increases linearly with the size of the error. The forecast that minimizes the expected absolute forecast error is the median, not the mean (or more precisely, the arithmetic average). If the mean and the median are the same, this is a distinction that does not matter. On the other hand, if the distribution is not symmetric, as the earnings distribution is not, the median is a better forecast than the mean if a forecast error's cost increases linearly with the forecast error.<sup>19</sup>

Analysts do not make forecasts in isolation. Other analysts are making forecasts as well, and the existence of other forecasts can affect an analyst's forecasts in many ways. A simple, common forecasting game illustrates that an unbiased forecast may not be an analyst's best forecast. Consider a forecasting game in which the smallest forecast error wins and receives a prize; everyone else receives nothing. Analysts' situations may be closer to this game than to isolated forecasts. In this game, the incentive is to be the closest. If you are not the closest, then it matters not at

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<sup>18</sup>A minimum expected absolute error forecast minimizes  $E|e|$ .

<sup>19</sup>Gu and Wu (2003) discuss this in more detail.

all whether your forecast error is almost as good as the best or is far away. More generally, any analyst's forecast will depend on what they think other people will forecast or what others have forecasted. A simple example is one in which two people guess someone else's pick of a number between zero and ten. The unbiased forecast is five. Suppose that the first person picks five. If the second person picks five, then he cannot win, only tie. A pick of either four or six can increase the expected winnings of the person going second if there is no payoff from tying. Neither four nor six is unbiased, but that doesn't matter. Either number maximizes expected winnings and it is winnings that matter.

This suggests that, even if analysts' forecasts are biased, it is important to consider analysts' incentives before denouncing them as 'irrational' or 'ignoring information readily available to them.'

Among others, Hong and Kubik (2003), Clarke and Subramanian (2006), Ottaviani and Sørensen (2006) and Ljungqvist et al. (2007) highlight factors that can explain a non-zero predictable forecast error. For example, Clarke and Subramanian (2006) suggest that an analyst doing poorly and at risk of being fired is more likely to make a "bold" forecast which is not likely to be correct but will save the analyst's job if it is correct.

## **Tests for Unbiasedness**

The proposition that analysts' forecasts are biased is simple to test with a test whether the average difference between actual earnings and forecasted earnings is zero.<sup>20</sup>

Given the evidence above that forecast errors are not symmetric, it is worthwhile to test whether the median forecast error is zero in addition to testing whether the

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<sup>20</sup>The test is a standard t-test of whether the mean forecast error equals zero using the asymptotic normal distribution.

mean forecast error is zero. The test that analysts' mean forecast errors are zero is a simple t-test. The test that analysts' median forecast errors are zero is the sign test for deviations from zero.

Table 5 presents the mean and median forecast errors by industry at the various horizons and p-values for tests whether the mean and median forecast errors are zero. The mean forecast errors are far smaller at the one-month horizon than at longer horizons. At the twelve-month horizon, the mean forecast error indicates that forecasted earnings are greater than actual earnings by about one cent per dollar of share price. At the one-month horizon, the mean forecast errors indicate that forecasted earnings are greater than actual earnings by about one-hundredth of a cent per dollar of stock price.

How big are these forecast errors? Mean earnings for all firms in our data are two cents per dollar of share price; median earnings are 3.9 cents per dollar of share price. A forecast error of one cent per dollar of share price at the twelve-month horizon is large relative to average earnings of two cents. A forecast error of one-hundredth of a cent at the one month horizon is relatively small, not obviously economically insignificant.

The median forecast error for all industries is minus nine-hundredths of a cent per dollar of share price at the twelve-month horizon. At the six-month and one-month horizons, the median forecast errors are minus two-hundredths of a cent per dollar of share price and three-hundredths of a dollar per dollar of share price. All these magnitudes based on the median are statistically significantly different from zero. Median forecast errors of hundredths of a cent per dollar of share price are not particularly large relative to median earnings of about four cents per dollar of share price.

There is substantial variation in the means and medians by industry. The mean forecast errors by industry mirror the overall mean forecast errors, declining in magni-

tude as the horizon shortens. The median forecast errors show substantial variability across industries in terms of magnitude. At the one-month horizon, all of the magnitudes are the same small order of magnitude as the overall median, with the largest being five hundredths of one cent per dollar of share price.

Table 6 shows the results of tests whether the average and median forecast errors are zero by year. With the exception of the last year in the table, 2004, all of the p-values for testing whether mean forecast errors are zero at the twelve-month horizon are less than  $10^{-4}$ . All mean forecast errors are negative, indicating that forecasts on average are greater than actual earnings. Mean forecasts six months ahead look much like the forecasts at the twelve-month horizon. The forecasts at the one-month horizon look quite a bit different. At the one-month horizon, there is little evidence in our data of bias in the mean forecast. Eight of the fifteen forecasts are positive and seven are negative. Nine of the forecasts are statistically significant at the five percent level, but they are not uniformly positive or negative. There is little evidence to support a conclusion that mean forecasts at the one-month horizon are uniformly above or below zero. These estimates provide little to no support for forecasts typically being under-estimates close to the announcement date.

The median forecasts in Table 6 are closer to zero than the mean forecasts. The results of the statistical tests that the median forecasts equal zero indicate that they are not zero, but the magnitudes generally are hundredths of a cent per dollar of share price.

At the twelve-month horizon, the overall median forecast error is negative, but this masks interesting variation by year. In five years – 1995, 1999, 2000, 2003 and 2004, the median forecast error at the twelve-month horizon is positive, indicating that the median analyst underestimated the level of earnings. This is the opposite of the bias in the mean forecast. It is interesting that these years are toward the end of the period. For four years – 1995, 1996, 1999, and 2002, the median forecast error is

not statistically significantly different from zero at the five percent significance level. Two of these years have positive median forecast errors and two have negative ones. At this twelve-month horizon, only eight of the fifteen years have median forecast errors that are negative and statistically significant. Moreover, of the medians at this twelve-month horizon from 1999 to 2004, only the recession year 2001 has a negative median forecast error that is statistically significantly different than zero; three of the five years have positive median forecast errors that are statistically significant. These results are consistent with the median forecast errors not being zero always, but there is little support for the median forecasts uniformly being too high or too low.

At the six-month horizon, median forecast errors also provide strong support for typical over-estimation of earnings. The median forecast errors are negative in eight of the fifteen years, barely more than half the fifteen years. The median forecast errors are positive and statistically significant at the five percent significance level in years, 1996, 1997, 1999, 2000 and 2003.

At the one-month horizon, the median forecast errors are positive in all years but 1990, a result consistent with the stylized view in the literature that forecast errors are underestimates close to the announcement. It is interesting that our data support such an inference using medians but provide much less support with means. All of the median forecast errors at the one-month horizon are quite small, never larger in magnitude than four-hundredths of a cent per dollar of share price. Economically, this is not that far from zero.

## CONCLUSION

Our data for U.S. analysts' forecasts of U.S. firm's earnings from 1990 through 2004 show typical results: analysts' forecasts are greater than earnings on average a year before earnings are announced. This conclusion is supported by both means and medians. Six months before the earnings announcements, mean earnings forecasts

are greater than actual earnings but median earnings forecasts are about as likely to be above actual earnings as below them. Our results show some unexpected results also. A month before the announcement, mean forecast errors provide little support for predictable differences between earnings and forecasts. Median forecast errors at the one-month horizon generally are positive and statistically significant, indicating that the median analysts' forecast is less than earnings on average. These median forecast errors are relatively small in magnitude though, on the order of hundredths of pennies of earnings relative to the share price when average and median earnings are about two and four cents relative to the share price.

Mean forecast errors and median forecast errors differ substantially. The distribution of forecast errors is asymmetric, with mean forecast errors being substantially larger in magnitude than median forecast errors at the six-month and twelve-month horizons. The distribution of earnings themselves is asymmetric. The distribution of earnings forecasts also is asymmetric but not sufficiently asymmetric that forecast errors are symmetric. There are substantial differences in mean and median forecast errors across industries. We also find substantial differences in mean and median forecast errors by year, with the largest forecast errors in recession years.

## REFERENCES

- Bera, Anil K. and Carlos M. Jarque. 1980. "Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals." *Economics Letters*, 6(3) (October) pp. 255-259.
- Boni, L. A. and Womack, K. L. 2002. "Wall Street's Credibility Problem: Misaligned Incentives or Dubious Fixes?" *Brookings - Wharton Papers on Financial Services* 160, pp. 93-124.
- Clarke, Jonathon, and Ajay Subramanian. 2006 "Dynamic Forecasting Behavior by Analysts: Theory and Evidence." *Journal of Financial Economics* 80 (April), pp. 81-113.
- Dwyer, Jr., Gerald P., and Cesare Robotti. 2004. "The News in Financial Assets' Returns." Federal Reserve Bank of Atlanta *Economic Review* 89 (First Quarter), 1-23.
- Ehrbeck, Tilman, and Robert Waldmann. 1996. "Why Are Professional Forecasters Biased? Agency Versus Behavioral Explanations." *Quarterly Journal of Economics* 111 (February), pp. 21-40.
- Elton, E. J., and M. J. Gruber. 1971. "Improved Forecasting Through the Design of Homogenous Groups." *Journal of Business* 44 (4), pp. 432-50.
- Elton, E. J., and M. J. Gruber. 1970. "Homogeneous Groups and Testing of Economic Hypotheses." *Journal of Financial and Quantitative Analysis* 4 (January), pp. 581-602.
- Frankel, Richard, S. P. Kothari and Joseph Weber. 2006. "Determinants of the Informativeness of Analyst Research." *Journal of Accounting and Economics* 41 (April), pp. 29-54.

- Gu, Zhaoang, and Joanna Shuang Wu. 2003. "Earnings Skewness and Analyst Forecast Bias." *Journal of Accounting and Economics* 35 (April), 5-29.
- Gupta, M. K. 1967. "An Asymptotically Nonparametric Test of Symmetry." *Annals of Mathematical Statistics* 38 (June), pp. 849–866.
- Hong, Harrison, and Jeffrey D. Kubik. 2003. *Journal of Finance* 58 (February), pp. 313-51.
- Keane, Michael P. and Runkle, David E. 1990. "Testing the Rationality of Price Forecasts: New Evidence from Panel Data." *American Economic Review* 80 (Month), pp. 714–735.
- Keane, Michael P. and David E. Runkle. 1998. "Are Financial Analysts' Forecasts of Corporate Profits Rational?" *Journal of Political Economy* 160 (September), pp. 768–805.
- Kolasinski, Adam C. and S. P. Kothari. 2006. "Investment Banking and Analyst Objectivity: Evidence from Analysts Affiliated with M&A Advisors." Unpublished paper, Massachusetts Institute of Technology.
- Kothari, S. P., Jonathan Lewellen and Jerold B. Warner. 2006. "Stock Returns, Aggregate Earnings Surprises, and Behavioral Finance." *Journal of Financial Economics* 79 (March), pp. 537-68.
- Ljungqvist, Alexander, Felicia Marston, Laura T. Starks, Kelsey D. Weid and Hong Yan. 2005. "Conflicts of Interest in Sell-side Research and the Moderating Role of Institutional Investors." *Journal of Financial Economics*, forthcoming.
- Ottaviani, Marco, and Peter Norman Sørensen. 2006. "The Strategy of Professional Forecasting." *Journal of Financial Economics* 81 (August), 441-66.



Sirri, Erik. 2004. "Investment Banks, Scope, and Unavoidable Conflicts of Interest."  
Federal Reserve Bank of Atlanta *Economic Review* 89 (Fourth Quarter), 23-35.

Smith, Randall, Kara Scannell and Paul Davies. 2007. "A 'Brazen' Insider Scheme Revealed." *Wall Street Journal* (March 2), pp. C1, C2.

Table 1  
Summary of Minimum and Maximum Values and Observations Suppressed in Figures 1 and 2

Variable	<u>Twelve Month Horizon</u>			<u>Six Month Horizon</u>			<u>One Month Horizon</u>		
	Minimum	Maximum	Number of Suppressed Observations	Minimum	Maximum	Number of Suppressed Observations	Minimum	Maximum	Number of Suppressed Observations
Actual Earnings	-1.6137	0.2844	150	-1.1820	0.3350	58	-0.9026	0.2844	11
Earnings Forecasts	-1.1532	0.2933	76	-0.7732	0.3267	21	-0.6487	0.2778	10
Forecast Errors	-1.2442	0.7614	89	-1.1561	0.5533	15	-0.6085	0.3531	2

Note: For actual earnings and earnings forecasts there are no positive observations outside the -0.5 to +0.5 range. For forecast errors, there are 6, 2 and 0 excluded positive observations at the 12, 6, and 1 forecast horizon; the remaining are negative.

Table 2  
Distribution of Forecast Errors by Year and Horizon  
Twelve Month Horizon

	Minimum	1%	5%	10%	25%	Median	75%	90%	95%	99%	Maximum	Mean	Standard Deviation	Skewness Coefficient	Kurtosis
1990	-.81	-.4278	-.1265	-.0721	-.0249	-.0040	.0003	.0059	.0121	.0456	.09	-.0270	.0754	-4.98	31.33
1991	-.88	-.3711	-.1320	-.0770	-.0245	-.0048	.0002	.0068	.0177	.0667	.30	-.0249	.0711	-4.95	37.73
1992	-.40	-.2019	-.0922	-.0509	-.0158	-.0023	.0012	.0098	.0193	.0557	.12	-.0141	.0418	-3.53	18.96
1993	-.38	-.1789	-.0649	-.0367	-.0110	-.0011	.0022	.0088	.0185	.0636	.11	-.0095	.0368	-3.69	22.69
1994	-.47	-.1807	-.0629	-.0334	-.0091	-.0003	.0024	.0100	.0194	.0554	.17	-.0096	.0431	-6.08	52.96
1995	-.27	-.1297	-.0618	-.0367	-.0099	.0000	.0039	.0118	.0201	.0633	.18	-.0071	.0309	-2.50	16.08
1996	-.29	-.1455	-.0697	-.0379	-.0100	-.0001	.0032	.0134	.0256	.0593	.20	-.0078	.0337	-2.20	13.34
1997	-.45	-.1566	-.0608	-.0329	-.0093	-.0008	.0023	.0085	.0143	.0400	.11	-.0094	.0362	-5.56	49.00
1998	-.49	-.2378	-.0704	-.0495	-.0198	-.0035	.0010	.0060	.0131	.0419	.27	-.0154	.0422	-4.19	29.79
1999	-.76	-.2484	-.0743	-.0391	-.0119	.0000	.0050	.0224	.0430	.1306	.39	-.0079	.0576	-3.74	39.19
2000	-.51	-.2230	-.0752	-.0395	-.0120	.0003	.0055	.0276	.0634	.1277	.31	-.0054	.0508	-2.41	17.01
2001	-1.24	-.3840	-.1364	-.0785	-.0335	-.0086	.0007	.0091	.0208	.1803	.76	-.0265	.0895	-4.00	50.19
2002	-.74	-.2228	-.0656	-.0370	-.0114	-.0002	.0064	.0234	.0426	.0976	.32	-.0067	.0522	-5.09	53.33
2003	-.71	-.1839	-.0617	-.0339	-.0104	.0003	.0092	.0266	.0443	.0949	.28	-.0045	.0464	-3.98	38.24
2004	-.33	-.1148	-.0438	-.0212	-.0068	.0010	.0088	.0264	.0394	.0812	.14	-.0003	.0317	-3.10	26.77

Six Month Horizon

	Minimum	1%	5%	10%	25%	Median	75%	90%	95%	99%	Maximum	Mean	Standard Deviation	Skewness Coefficient	Kurtosis
1990	-1.16	-.2730	-.0955	-.0427	-.0122	-.0016	.0008	.0060	.0142	.0575	.20	-.0162	.0669	-7.95	92.95
1991	-.54	-.2171	-.0642	-.0353	-.0097	-.0015	.0009	.0074	.0176	.0600	.18	-.0108	.0441	-5.33	44.17
1992	-.32	-.1301	-.0444	-.0219	-.0071	-.0006	.0013	.0062	.0122	.0357	.11	-.0066	.0276	-5.01	39.50
1993	-.16	-.0814	-.0247	-.0137	-.0037	-.0001	.0018	.0066	.0142	.0409	.18	-.0024	.0181	-2.34	24.80
1994	-.17	-.0705	-.0284	-.0159	-.0041	.0000	.0024	.0076	.0129	.0400	.16	-.0025	.0170	-1.96	20.70
1995	-.30	-.0828	-.0330	-.0169	-.0044	.0000	.0022	.0065	.0111	.0293	.10	-.0038	.0198	-5.37	52.00
1996	-.32	-.0969	-.0287	-.0152	-.0038	.0001	.0024	.0090	.0151	.0389	.19	-.0029	.0227	-4.78	54.34
1997	-.27	-.0907	-.0275	-.0132	-.0030	.0001	.0023	.0079	.0146	.0422	.17	-.0021	.0206	-2.77	38.07
1998	-.33	-.0992	-.0359	-.0219	-.0081	-.0016	.0008	.0043	.0094	.0290	.29	-.0063	.0226	-3.18	49.61
1999	-.56	-.1600	-.0446	-.0202	-.0048	.0001	.0031	.0109	.0193	.0533	.55	-.0052	.0383	-3.74	78.39
2000	-.36	-.1101	-.0447	-.0221	-.0059	.0000	.0022	.0136	.0261	.0668	.17	-.0037	.0273	-2.68	26.48
2001	-.64	-.1714	-.0494	-.0274	-.0092	-.0015	.0012	.0074	.0141	.0581	.20	-.0085	.0391	-5.95	66.46
2002	-.38	-.0997	-.0325	-.0158	-.0054	-.0003	.0027	.0088	.0159	.0402	.21	-.0038	.0269	-6.09	76.24
2003	-.49	-.0994	-.0295	-.0140	-.0036	.0004	.0045	.0125	.0213	.0667	.38	-.0011	.0310	-2.52	68.31
2004	-.29	-.0617	-.0284	-.0184	-.0045	.0000	.0032	.0092	.0164	.0389	.09	-.0025	.0195	-5.05	57.05

One Month Horizon

	Minimum	1%	5%	10%	25%	Median	75%	90%	95%	99%	Maximum	Mean	Standard Deviation	Skewness Coefficient	Kurtosis
1990	-.61	-.0970	-.0286	-.0146	-.0031	-.0001	.0014	.0054	.0131	.0526	.22	-.0035	.0342	-11.48	204.59
1991	-.24	-.0659	-.0231	-.0111	-.0024	.0000	.0020	.0074	.0141	.0395	.13	-.0015	.0188	-2.99	48.29
1992	-.14	-.0698	-.0118	-.0053	-.0010	.0002	.0025	.0073	.0144	.0402	.24	.0006	.0220	4.09	61.43
1993	-.26	-.0659	-.0127	-.0064	-.0012	.0001	.0020	.0062	.0112	.0400	.10	-.0005	.0154	-4.97	71.88
1994	-.11	-.0274	-.0079	-.0039	-.0007	.0002	.0020	.0057	.0104	.0289	.09	.0006	.0102	-1.20	41.64
1995	-.22	-.0455	-.0093	-.0048	-.0009	.0002	.0019	.0057	.0114	.0390	.31	.0004	.0188	1.28	104.42
1996	-.20	-.0277	-.0078	-.0036	-.0005	.0003	.0017	.0054	.0097	.0482	.17	.0008	.0137	-.90	89.84
1997	-.36	-.0375	-.0114	-.0047	-.0006	.0003	.0019	.0054	.0096	.0325	.19	.0002	.0145	-6.48	217.27
1998	-.16	-.0256	-.0089	-.0044	-.0006	.0003	.0017	.0050	.0089	.0285	.20	.0004	.0102	1.12	110.97
1999	-.23	-.0410	-.0069	-.0031	-.0004	.0004	.0023	.0062	.0116	.0457	.28	.0011	.0158	1.31	118.62
2000	-.24	-.0673	-.0141	-.0057	-.0007	.0002	.0013	.0044	.0088	.0291	.11	-.0011	.0147	-6.61	83.84
2001	-.18	-.0371	-.0101	-.0038	-.0005	.0002	.0014	.0038	.0066	.0211	.08	-.0004	.0104	-6.24	94.52
2002	-.26	-.0340	-.0079	-.0036	-.0005	.0003	.0013	.0038	.0067	.0211	.35	-.0002	.0135	.63	268.15
2003	-.36	-.0645	-.0100	-.0047	-.0007	.0003	.0018	.0054	.0097	.0373	.15	-.0003	.0157	-7.81	145.27
2004	-.15	-.0333	-.0078	-.0037	-.0007	.0004	.0022	.0052	.0087	.0255	.15	.0006	.0092	.89	77.55

\* This test statistic has a Chi-square distribution with two degrees of freedom under the null hypothesis. The value of this Chi-square at the .001 level of significance is 13.8. All of the values in the table have  $p$ -values less than  $10^{-8}$ .

Table 3  
Sign Test Statistics and Skewness Coefficients by Year and Horizon

	<u>Sign Test</u>						<u>Skewness Coefficient</u>					
	12 Month Horizon		6 Month Horizon		1 Month Horizon		12 Month Horizon		6 Month Horizon		1 Month Horizon	
	Mean Minus Median	<i>p</i> -value	Mean Minus Median	<i>p</i> -value	Mean Minus Median	<i>p</i> -value	Coefficient	<i>p</i> -value	Coefficient	<i>p</i> -value	Coefficient	<i>p</i> -value
1990	-.0230	.0000	-.0146	.0000	-.0034	.0000	-5.806	.0000	-.370	.7116	-.024	.9807
1991	-.0201	.0000	-.0094	.0000	-.0015	.0000	-3.825	.0001	-2.375	.0176	-.014	.9885
1992	-.0118	.0000	-.0060	.0000	.0004	.0000	-16.085	.0000	-2.999	.0027	.337	.7360
1993	-.0085	.0000	-.0023	.0000	-.0006	.0000	-9.796	.0000	-5.912	.0000	-.183	.8546
1994	-.0092	.0000	-.0025	.0000	.0004	.0000	-2.374	.0176	-1.901	.0574	-.009	.9925
1995	-.0071	.0000	-.0038	.0000	.0001	.0007	-20.569	.0000	-1.532	.1256	.046	.9634
1996	-.0077	.0000	-.0030	.0000	.0005	.0000	-37.030	.0000	-1.409	.1588	-.049	.9611
1997	-.0086	.0000	-.0022	.0000	-.0002	.0000	-2.637	.0084	-2.637	.0084	-.017	.9867
1998	-.0120	.0000	-.0047	.0000	.0002	.0000	-14.384	.0000	-2.011	.0444	.008	.9933
1999	-.0079	.0000	-.0053	.0000	.0007	.0000	-3.588	.0003	-.552	.5812	.019	.9849
2000	-.0057	.0000	-.0037	.0000	-.0013	.0000	-24.850	.0000	-4.124	.0000	-.188	.8507
2001	-.0179	.0000	-.0070	.0000	-.0007	.0000	-2.469	.0136	-.864	.3877	.000	.9999
2002	-.0065	.0000	-.0035	.0000	-.0004	.0000	-1.841	.0657	-.721	.4708	.002	.9987
2003	-.0048	.0000	-.0015	.0000	-.0006	.0000	-2.926	.0034	-.415	.6780	-.081	.9358
2004	-.0013	.0000	-.0025	.0000	.0002	.0026	-7.336	.0000	-1.362	.1731	.033	.9739

Table 4  
*p*-values for Sign Test by Industry, Year and Horizon

Twelve Month Horizon

	All Industries	Energy	Telecom. Services	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Utilities
1990	.0000	.9188	.1877	.0000	.0000	.0000	.0000	.0001	.0000	.0000	.0021
1991	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
1992	.0000	.0000	.0789	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0184
1993	.0000	.0013	.8714	.0000	.0000	.0000	.0000	.0000	.0011	.0000	.0764
1994	.0000	.0000	.0396	1.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
1995	.0000	.0000	.1439	.1676	.0000	.0000	.0000	.0000	.0000	.0000	.6241
1996	.0000	.0002	.0300	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.8358
1997	.0000	.0065	.0163	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
1998	.0000	.0000	.0375	.0008	.0000	.0000	.0000	.0000	.0000	.0000	.0582
1999	.0000	.0669	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.3526
2000	.0000	.3435	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
2001	.0000	.0000	.7069	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.2578
2002	.0000	.0000	.0000	.0232	.0000	.0000	.0000	.0048	.0000	.0000	.0000
2003	.0000	.1454	.0000	.0000	.0000	.0000	.3284	.0000	.0000	.8904	.0055
2004	.0000	.0017	.1953	.0120	.0000	.0000	.0034	.0000	.0033	.0000	.0000

### Six Months Horizon

	All Industries	Energy	Telecom. Services	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Utilities
1990	.0000	.0154	.8318	.0000	.0000	.0000	.0000	.0001	.0000	.0000	.0000
1991	.0000	.0000	.0001	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0013
1992	.0000	.0111	.0037	.0000	.0000	.0000	.0000	.0012	.0000	.0000	.0199
1993	.0000	.0000	.0026	.0578	.0000	.0000	.0000	.0252	.0000	.0000	.8199
1994	.0000	.0000	.4188	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.3481
1995	.0000	.0010	.0000	.0000	.0000	.0000	.0004	.0000	.0000	.0000	.0854
1996	.0000	.0000	.0247	.0000	.0000	.0000	.7520	.0000	.0000	.0000	.0165
1997	.0000	.2458	.0275	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0104
1998	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0279	.0000	.0000	1.0000
1999	.0000	.0243	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0594
2000	.0000	.0039	.0013	.0000	.0000	.0000	.0011	.0000	.0000	.0000	.0010
2001	.0000	.0000	.0000	.0026	.0000	.0000	.4709	.0000	.0000	.0000	.0241
2002	.0000	.0230	.0013	.0003	.0000	.0000	.0015	.0000	.0000	.0000	.0000
2003	.0000	.9016	.0006	.8115	.0000	.0000	.0065	.0000	.0000	.0000	.0505
2004	.0000	.0013	.0000	.0353	.0000	.0000	.0000	.0002	.0000	.0000	.3153



One Month Horizon

	All Industries	Energy	Telecom. Services	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Utilities
1990	.0000	.0000	.3449	.0487	.0002	.0012	.0015	.3105	.0000	.0000	.0094
1991	.0000	.0000	1.0000	.0002	.0422	.0000	.0000	1.0000	.4096	.0336	.0000
1992	.0000	.0000	.0525	.6587	.1354	.0001	.0003	.0186	.0000	.0000	.0315
1993	.0000	.0001	.0241	.5728	.0000	.0005	.0046	.0950	.0005	.0000	.6201
1994	.0000	.0000	1.0000	.5703	.0000	.0232	.7660	.0003	.0005	.0000	.0073
1995	.2227	.0004	.0854	.0000	.0000	.0000	.0000	.0000	.0000	.0000	1.0000
1996	.0000	.0000	.0000	.0000	.0054	.0000	.0153	.0000	.0000	1.0000	.0088
1997	.0000	.0036	.0000	.0320	.0000	.0000	.0000	.0000	.0000	.0000	.0086
1998	.0000	.0000	.0000	.4445	.0185	.0000	.0007	.0000	.7699	.0143	.0317
1999	.0000	.0090	.0000	.0000	.0223	.0000	.0025	.0000	.6227	.0000	.0002
2000	.0000	.2925	.0474	.0000	.0000	.0055	.0000	.0000	.0000	.0000	.7465
2001	.0000	.0000	.0000	.2786	.8799	.0000	.1839	.0000	.0000	.0124	.9345
2002	.0000	.5934	.0000	.2429	.0000	.0000	1.0000	.9047	.0000	.0000	.0000
2003	.0000	.0000	.0125	.9307	.0000	.0000	.8243	.9502	.0000	.0335	.0261
2004	.0019	.0031	.0000	.0005	.0000	.0000	.5515	.0000	.0000	.7662	.0000

Table 5  
Forecast Errors By Industry and Horizon

	<u>12 Month Horizon</u>				<u>6 Month Horizon</u>				<u>1 Month Horizon</u>			
	Mean	<i>p</i> -value Mean Equals Zero	Median	<i>p</i> -value Median Equals Zero	Mean	<i>p</i> -value Mean Equals Zero	Median	<i>p</i> -value Median Equals Zero	Mean	<i>p</i> -value Mean Equals Zero	Median	<i>p</i> -value Median Equals Zero
All Industries	-.0106	.0000	-.0009	.0000	-.0048	.0000	-.0002	.0000	-.0001	.3456	.0003	.0000
Consumer Discretionary	-.0124	.0000	-.0017	.0000	-.0070	.0000	-.0009	.0000	-.0002	.3400	.0003	.0000
Consumer Staples	-.0067	.0000	-.0003	.0000	-.0039	.0000	-.0001	.0078	-.0002	.4837	.0002	.0000
Energy	-.0002	.8012	.0002	.1833	-.0015	.0001	-.0003	.0172	.0003	.4056	.0005	.0000
Financials	-.0101	.0000	.0000	.2480	-.0050	.0000	.0001	.0000	-.0005	.0410	.0002	.0000
Health Care	-.0043	.0000	.0000	.6499	-.0017	.0001	.0001	.0000	.0002	.5447	.0002	.0000
Industrials	-.0163	.0000	-.0025	.0000	-.0092	.0000	-.0012	.0000	.0007	.0372	.0003	.0000
Information Technology	-.0159	.0000	-.0016	.0000	-.0043	.0000	.0000	.5310	-.0004	.0890	.0003	.0000
Materials	-.0208	.0000	-.0084	.0000	-.0078	.0000	-.0027	.0000	.0003	.2840	.0004	.0000
Telecommunication Services	-.0099	.0000	-.0018	.0000	-.0043	.0001	-.0002	.0131	-.0009	.2061	.0002	.0001
Utilities	-.0050	.0000	-.0009	.0000	-.0021	.0062	-.0003	.0220	-.0006	.0732	.0001	.0004

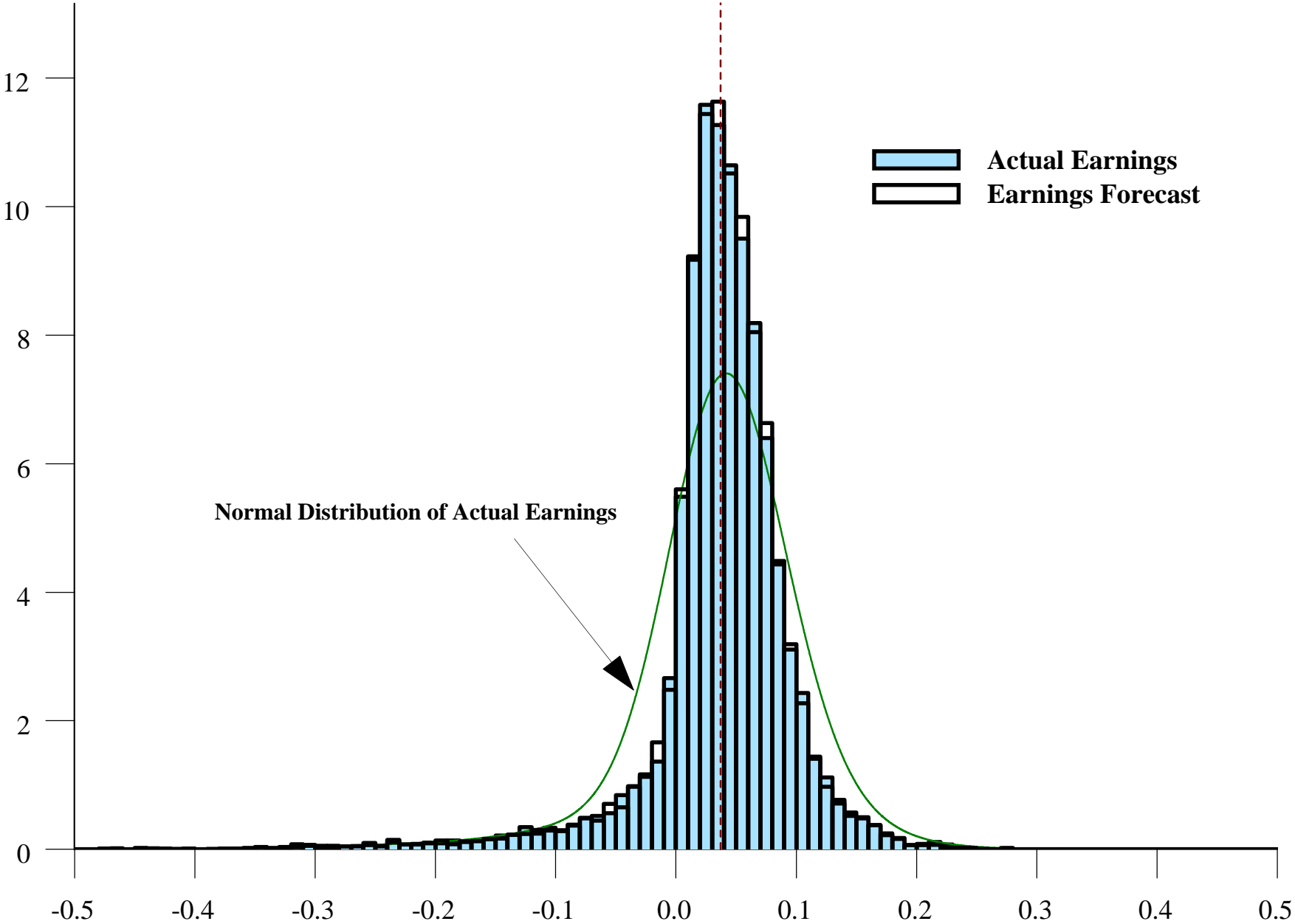
Table 6  
Forecast Errors By Year and Horizon

	<u>12 Month Horizon</u>				<u>6 Month Horizon</u>				<u>1 Month Horizon</u>			
	Mean	<i>p</i> -value Mean Equals Zero	Median	<i>p</i> -value Median Equals Zero	Mean	<i>p</i> -value Mean Equals Zero	Median	<i>p</i> -value Median Equals Zero	Mean	<i>p</i> -value Mean Equals Zero	Median	<i>p</i> -value Median Equals Zero
1990-2004	-.0111	.0000	-.0010	.0000	-.0048	.0000	-.0002	.0000	-.0000	.7701	.0003	.0000
1990	-.0270	.0000	-.0040	.0000	-.0162	.0000	-.0016	.0000	-.0035	.0016	-.0001	.0253
1991	-.0249	.0000	-.0048	.0000	-.0108	.0000	-.0015	.0000	-.0015	.0286	.0000	.5331
1992	-.0141	.0000	-.0023	.0000	-.0066	.0000	-.0006	.0000	.0006	.4243	.0002	.0001
1993	-.0095	.0000	-.0011	.0000	-.0024	.0000	-.0001	.0012	-.0005	.1985	.0001	.0000
1994	-.0096	.0000	-.0004	.0000	-.0025	.0000	.0000	.6343	.0006	.0062	.0002	.0000
1995	-.0071	.0000	.0000	.6729	-.0038	.0000	.0000	.1360	.0004	.3581	.0003	.0000
1996	-.0078	.0000	-.0001	.2249	-.0029	.0000	.0001	.0117	.0008	.0069	.0004	.0000
1997	-.0094	.0000	-.0008	.0000	-.0021	.0000	.0001	.0019	.0002	.6129	.0004	.0000
1998	-.0155	.0000	-.0035	.0000	-.0063	.0000	-.0016	.0000	.0004	.0338	.0003	.0000
1999	-.0079	.0000	.0000	.8265	-.0052	.0000	.0001	.0015	.0011	.0008	.0004	.0000
2000	-.0054	.0000	.0003	.0024	-.0037	.0000	.0000	.0106	-.0011	.0002	.0002	.0000
2001	-.0265	.0000	-.0086	.0000	-.0085	.0000	-.0015	.0000	-.0004	.0297	.0002	.0000
2002	-.0067	.0000	-.0002	.1688	-.0038	.0000	-.0003	.0001	-.0002	.5212	.0003	.0000
2003	-.0045	.0000	.0003	.0289	-.0011	.0669	.0004	.0000	-.0003	.3086	.0003	.0000
2004	-.0003	.5223	.0010	.0000	-.0025	.0000	.0000	.2696	.0006	.0012	.0004	.0000

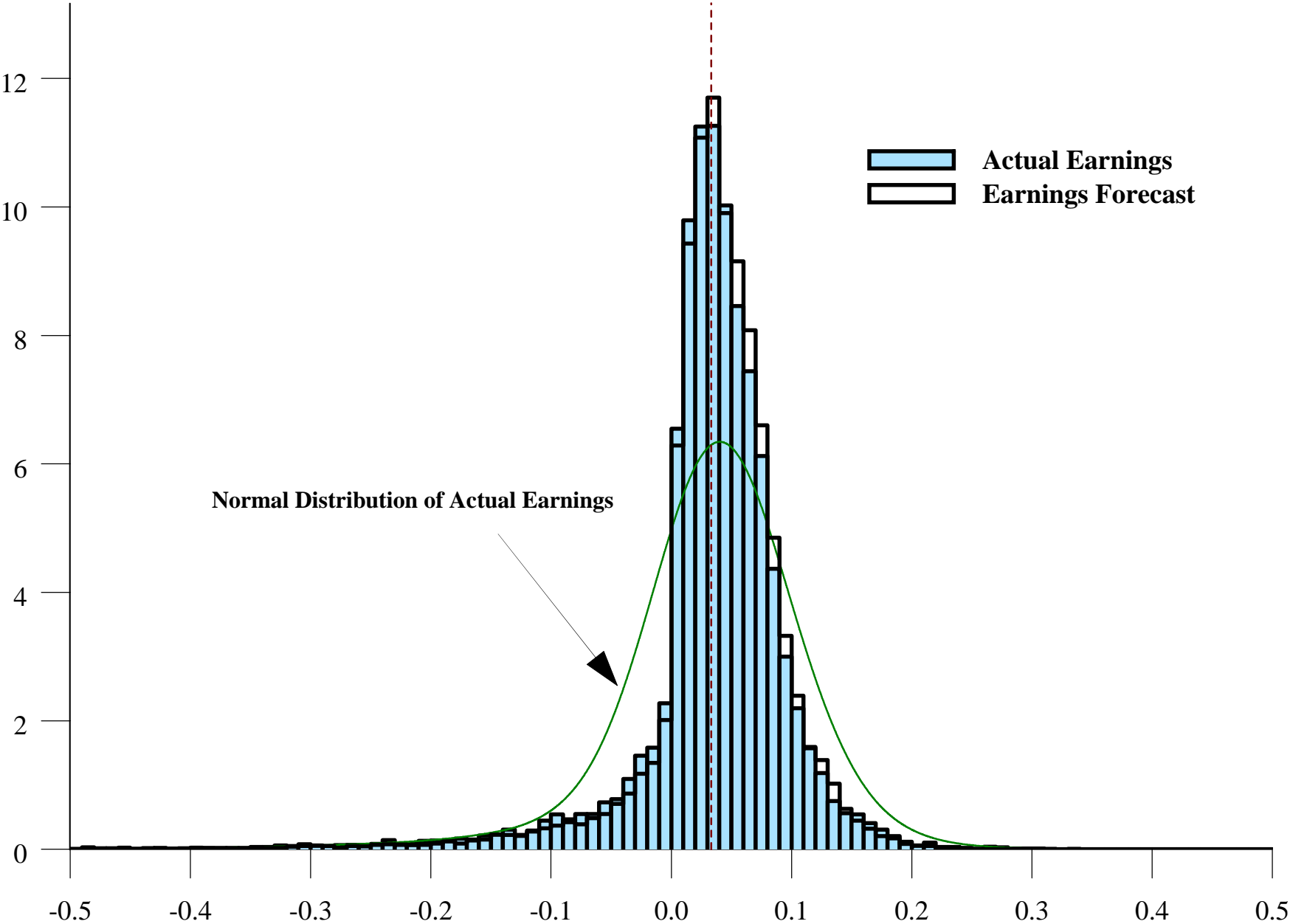
Appendix Table 1  
Number of Companies by Year  
(Companies Whose Fiscal Year Ends in December)

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Total
Entire Sample	1446	1451	1570	1827	2124	2240	2579	2883	2969	2759	2682	2577	2514	2546	2569	6574
<u>By Industry:</u>																
Consumer Discretionary	141	138	151	196	261	291	314	352	360	344	308	270	273	300	304	803
Consumer Staples	39	44	43	54	58	57	63	77	83	80	66	57	64	62	66	163
Energy	67	83	79	88	106	111	127	140	150	141	129	142	155	170	168	354
Financials	277	259	296	351	382	376	453	457	480	473	463	467	521	580	593	1366
Health Care	71	79	112	141	171	171	230	309	328	299	289	356	359	357	380	793
Industrials	177	186	194	203	226	243	251	284	333	305	287	253	252	260	272	706
Information Technology	96	101	106	133	175	208	297	373	388	372	488	499	447	416	421	1062
Materials	108	106	108	118	131	150	160	162	166	153	144	129	126	123	121	303
Telecommunication Services	21	18	25	28	32	32	39	60	65	60	64	55	47	43	47	170
Utilities	70	68	68	78	76	76	77	79	82	83	77	82	74	80	83	167
Sum of Industries:	1067	1082	1182	1390	1618	1715	2011	2293	2435	2310	2315	2310	2318	2391	2455	5887

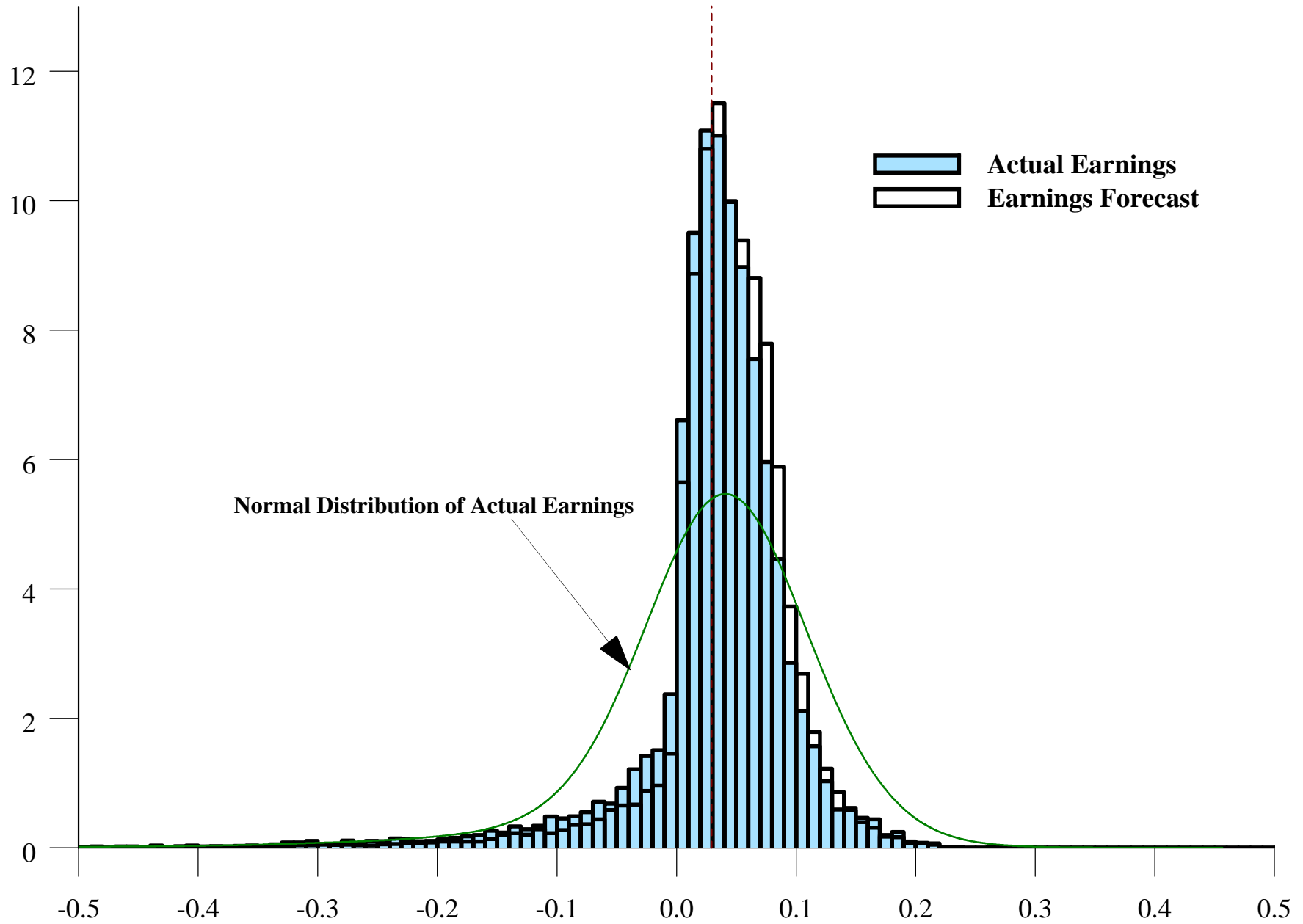
**Figure 1**  
**Actual Earnings and Earnings Forecast**  
Panel 1: Forecast Horizon of One Month



**Figure 1**  
**Actual Earnings and Earnings Forecast**  
Panel 2: Forecast Horizon of 6 Months



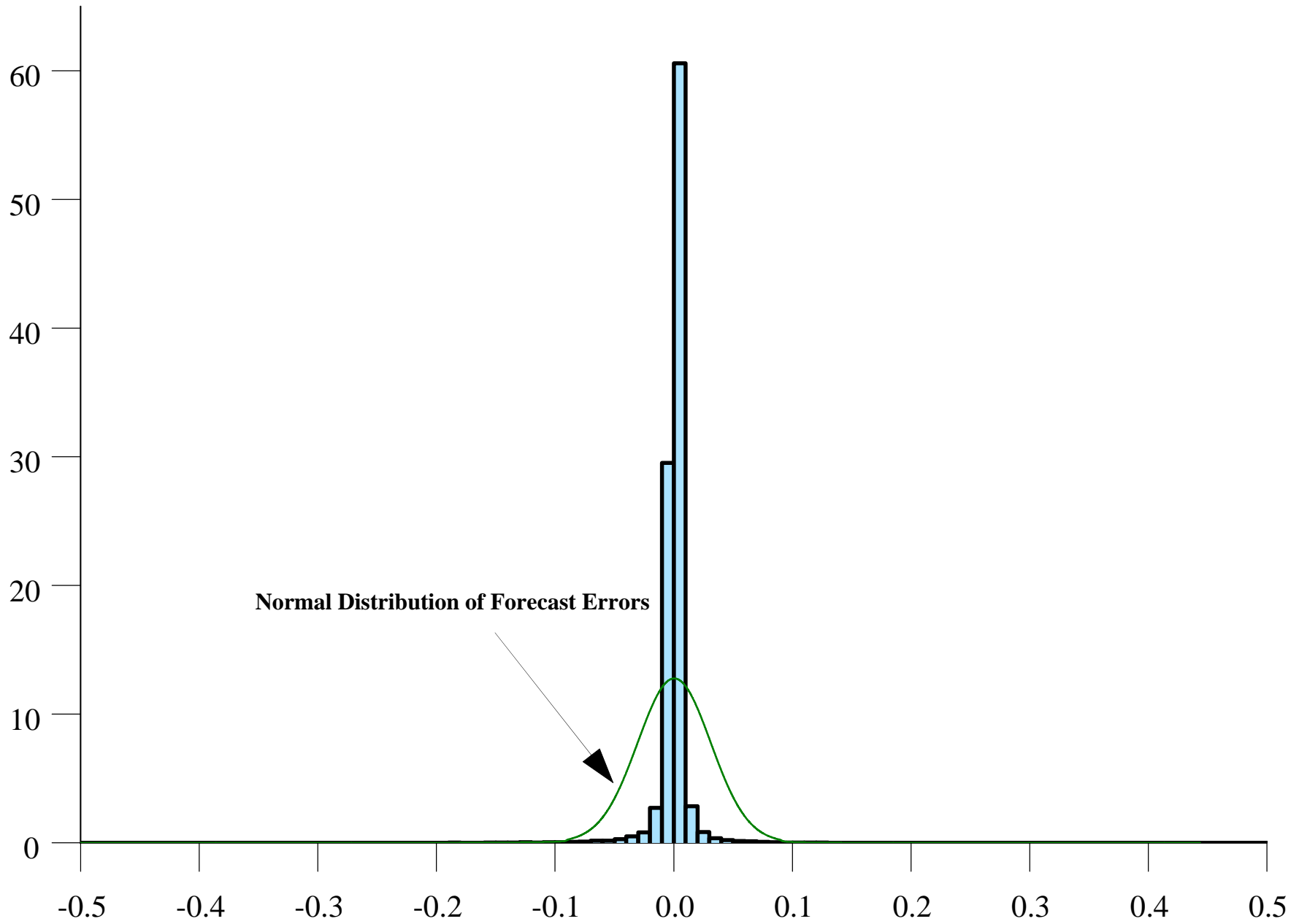
**Figure 1**  
**Actual Earnings and Earnings Forecast**  
Panel 3: Forecast Horizon of 12 Months



# Figure2

## Forecast Errors

Panel 1: Forecast Horizon of One Month

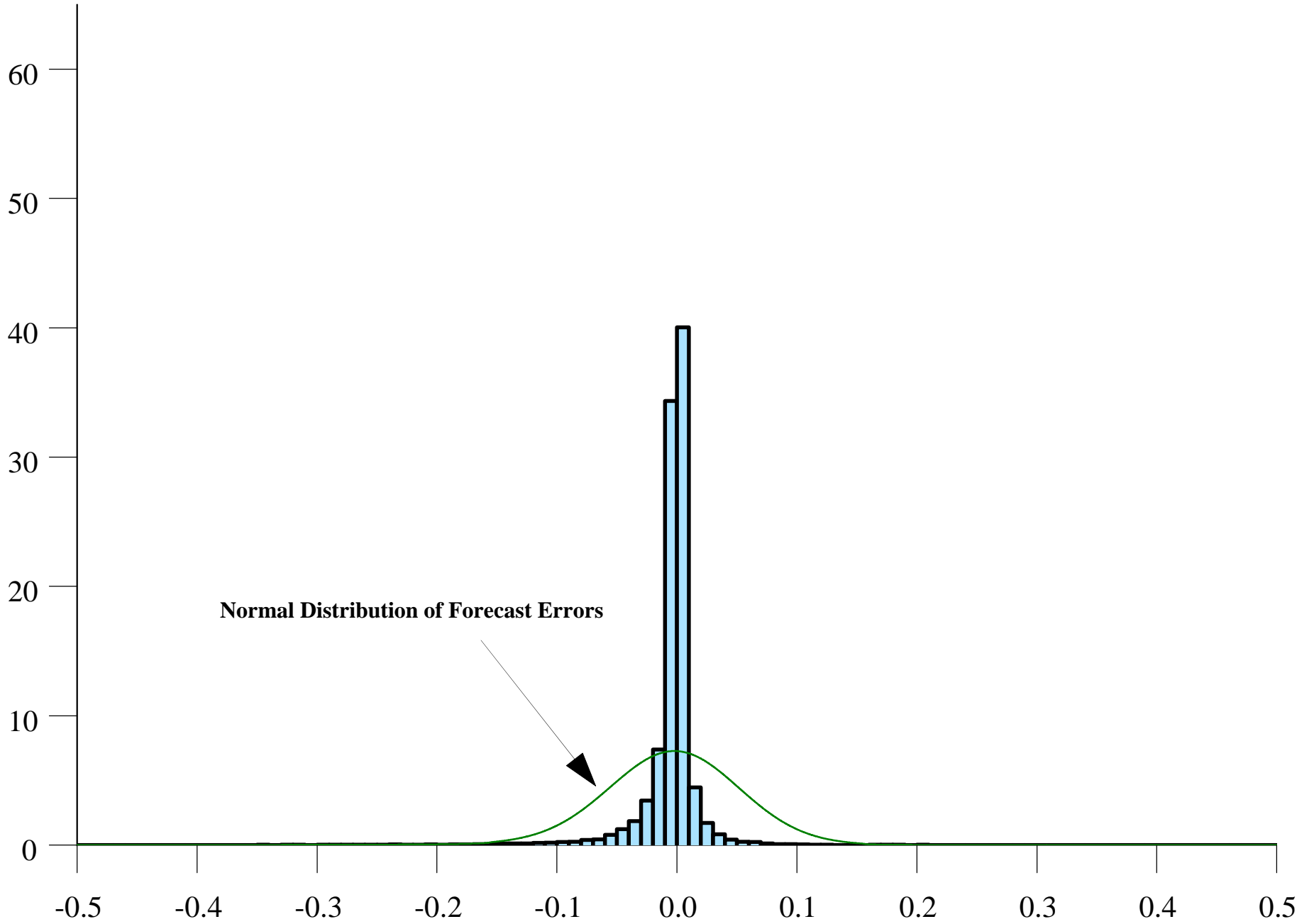




# Figure 2

## Forecast Errors

Panel 2: Forecast Horizon of 6 Months



# Figure 2

## Forecast Errors

Panel 3: Forecast Horizon of 12 Months

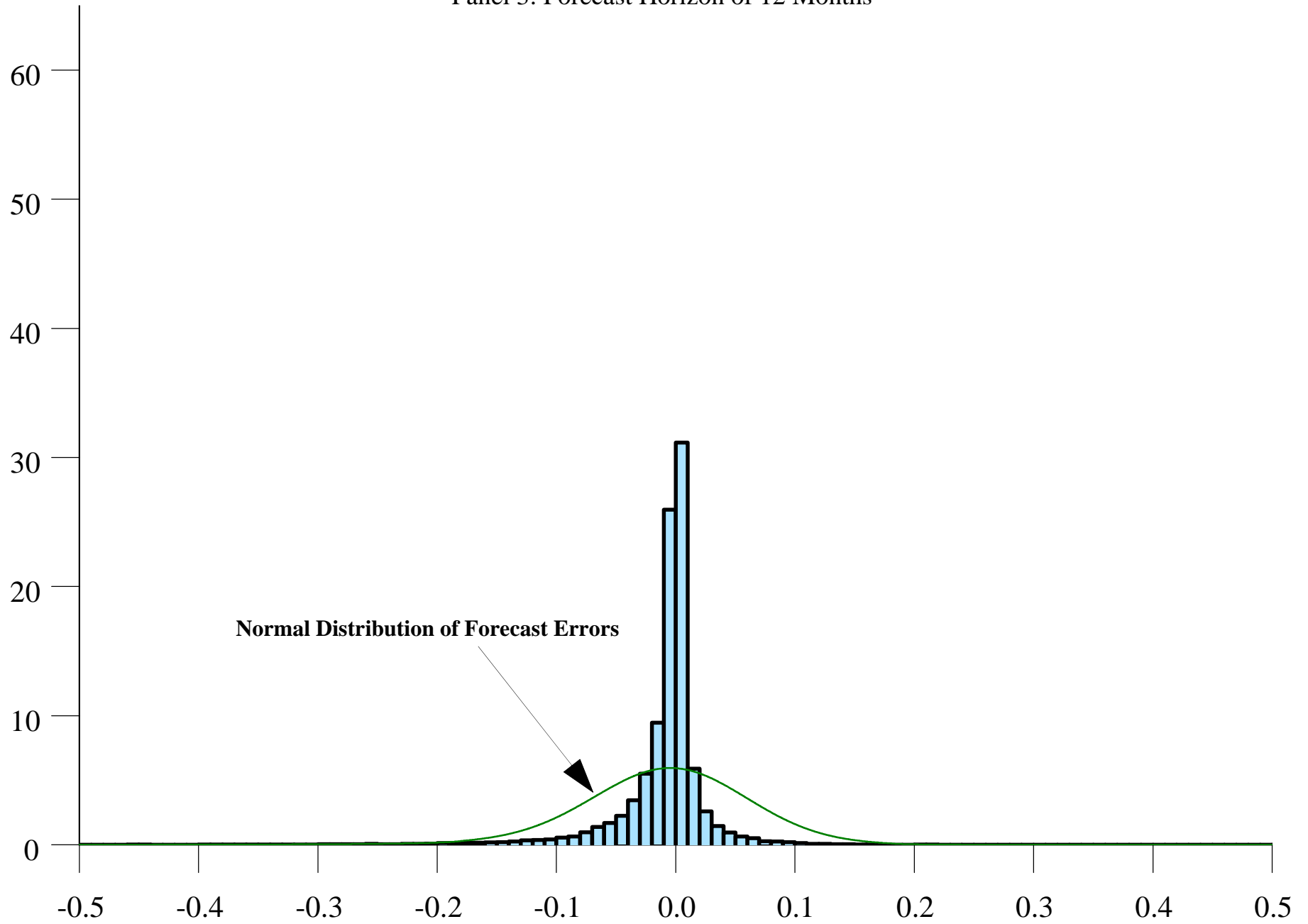


Figure 3  
Forecast Errors By Horizon

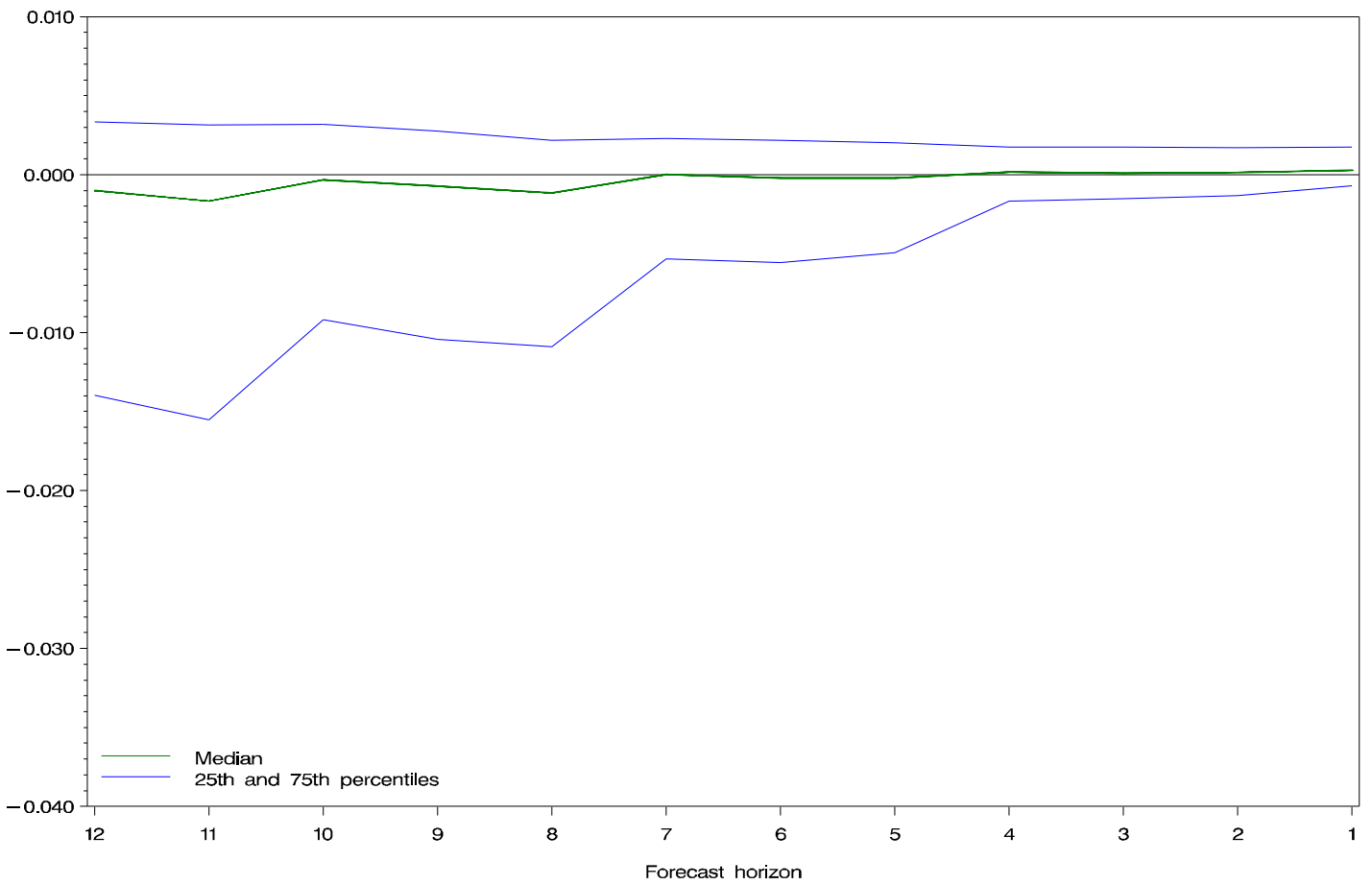
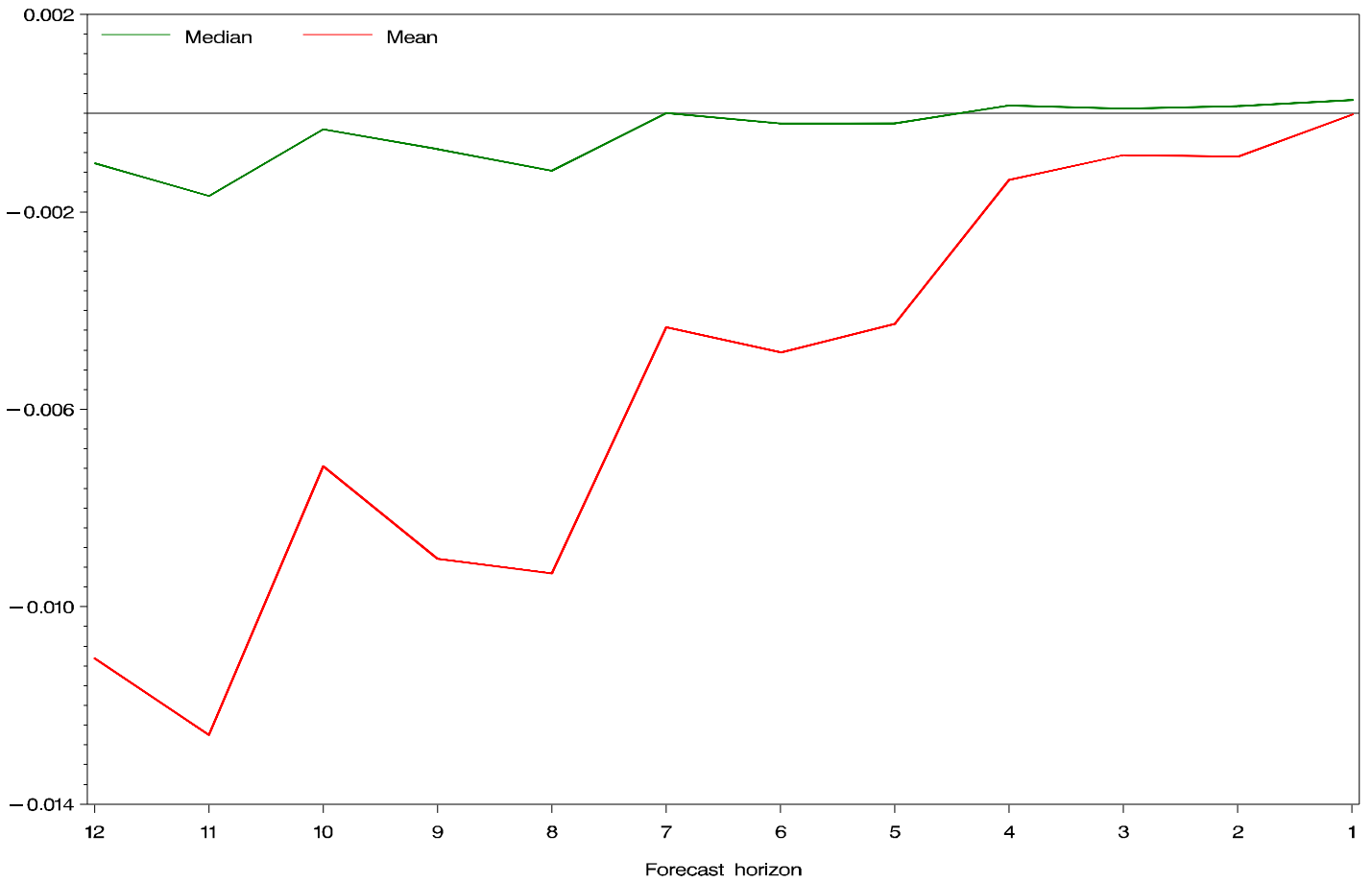


Figure 4  
Distribution of Forecast Errors by Year and Horizon

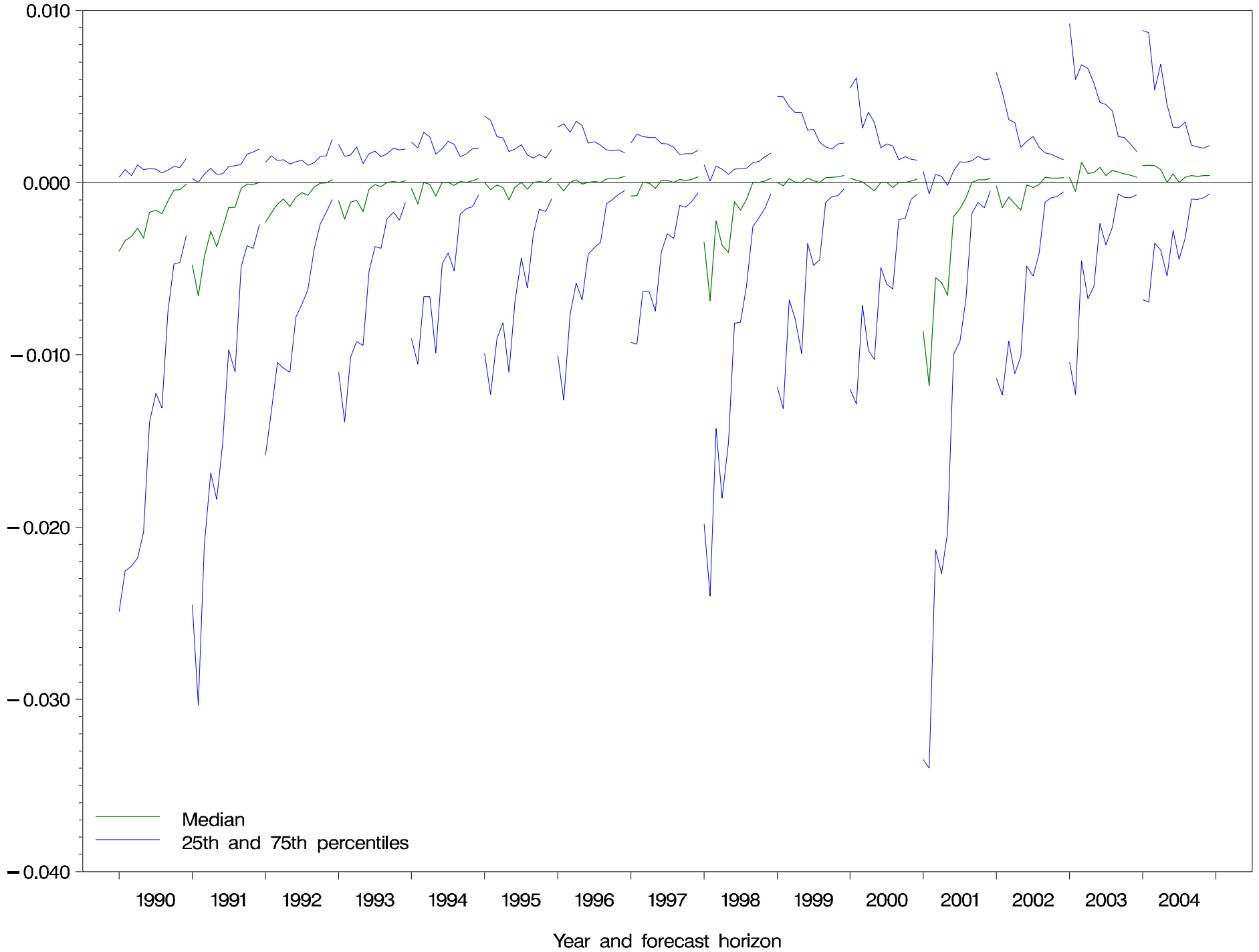


Figure 5  
Distribution of Forecast Errors by Year and Horizon and Industry  
Part 1

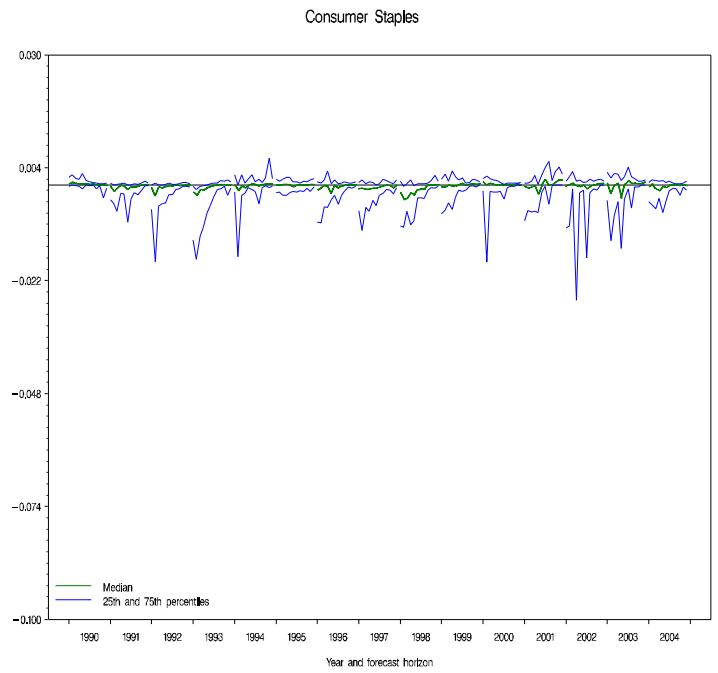
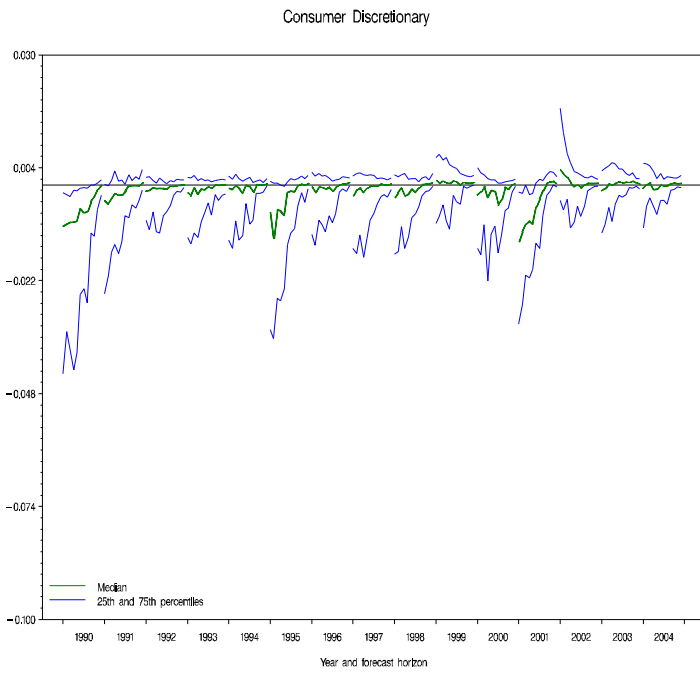
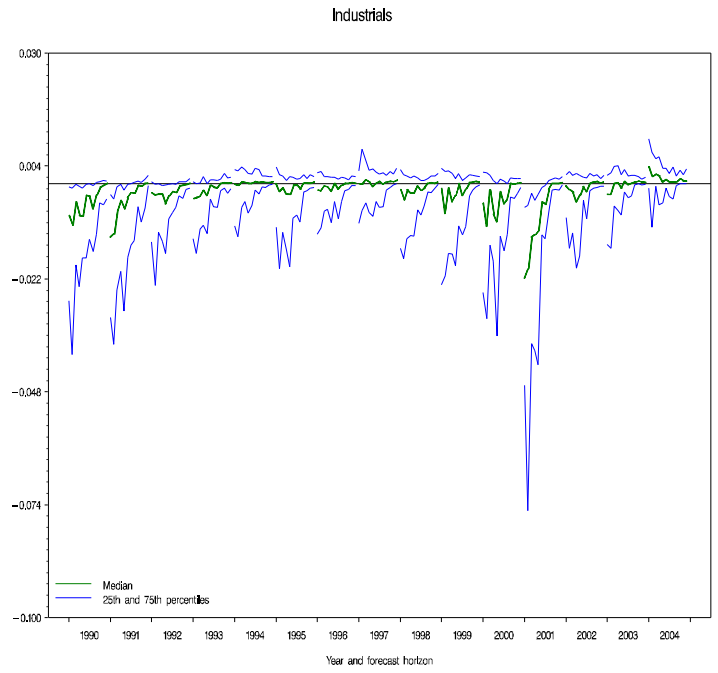
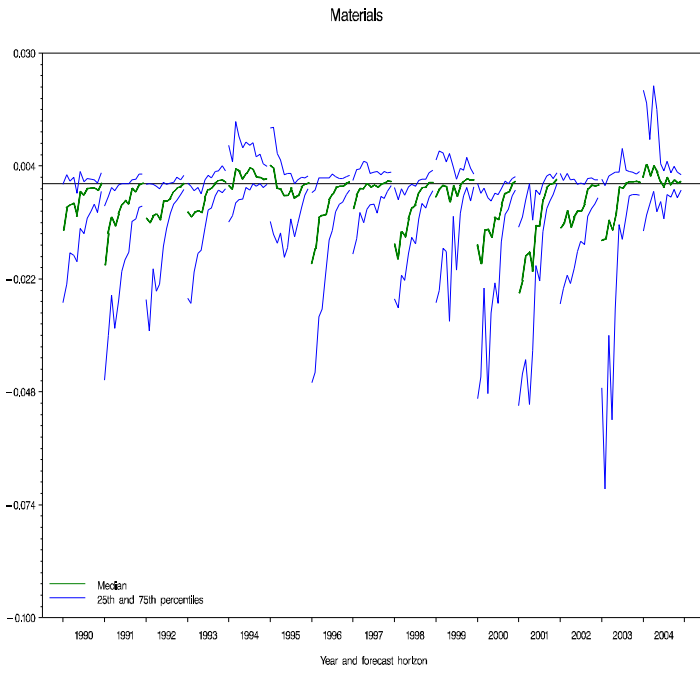


Figure 5  
Distribution of Forecast Errors by Year and Horizon and Industry  
Part 2

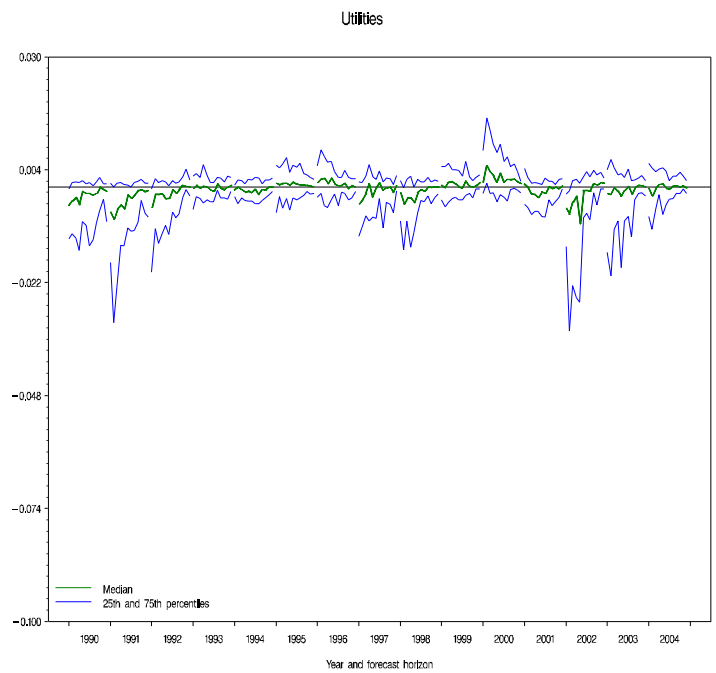
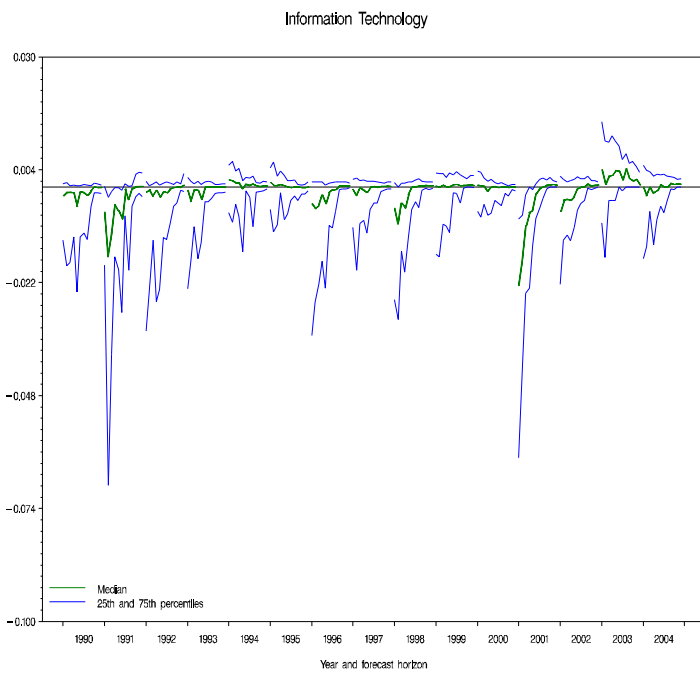
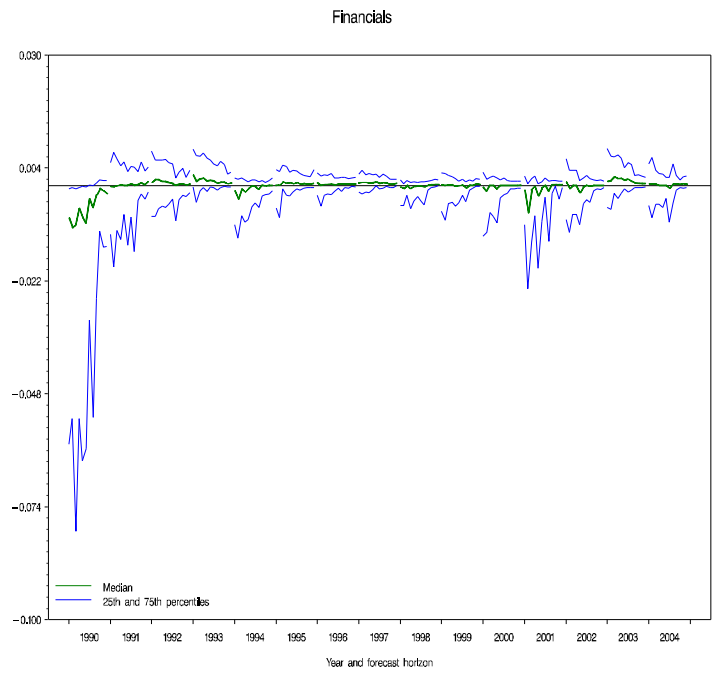
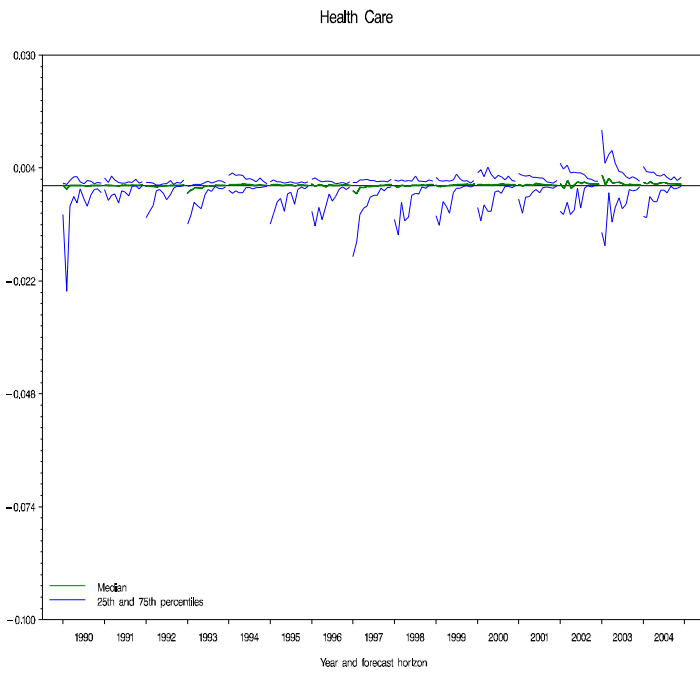


Figure 5  
Distribution of Forecast Errors by Year and Horizon and Industry  
Part 3

