# On the Term Structure of Loss Preference Asymmetry in Earnings Forecasts

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## Abstract

Using time series of forecast errors for a large number of US companies, we estimate the parameter of the implicit loss function in sixteen cases for each company, that is, four different forecast types across four different forecast horizons. Our results allowed the formation of an empirical cross sectional distribution of loss preference parameters in each of the sixteen forecast type vs. horizon combinations. We find that analysts have asymmetric loss functions. Normality is rejected in twelve out of sixteen cases, particularly due to the presence of skewness. For all types of forecasts we observe statistically significant, monotonic in direction, differences across the distributions of different forecast horizons. These findings document a heterogeneity of forecast loss preferences across forecast horizons, which is consistent with the "walk-down" effect of being on average optimistic for long-run predictions, turning pessimistic for short-run ones.

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## 1. Introduction

The bias in corporate earnings forecasts as an empirical stylised fact has been documented widely in the literature. An immediate definition of bias stems from the average statistical discrepancy between the forecasts and the mean realized earnings, which in the early literature has often be characterized as irrational. However, reflecting on Lo (1999) on the three P's of total risk management, a more complete understanding would need to consider jointly the three key aspects of forecast optimality: data, loss preferences and probability distributions. In this respect, the original work on asymmetric loss functions of Granger (1969) and its extensions by Christofersen and Diebold (1997) and Christodoulakis (2005, 2006) on non-normality, show that such deviations from the mean constitute a rational forecast bias that can optimize the forecaster's objective function. Thus, many of the existing empirical conclusions on the irrationality of earnings forecasts may weaken or collapse. In particular, as financial analysts produce earnings forecasts on a regular basis for large number of companies, not all of them forecast optimistically or pessimistically at the same time. If one could observe their forecast loss preferences, a natural empirical distribution would emerge, indicating their central tendencies, dispersion, asymmetries and extremes, among other features. Furthermore, such a distribution of forecast preferences may be varying across different forecast horizons.

In this paper, our access to the IBES database for US company earnings concerns forecasts of horizons from one to four quarters that are all generated on a quarterly basis. We observe time series of forecast errors for each individual company, for sixteen combinations of forecast type vs. horizon and utilise the methodology of Elliott et al (2005) to estimate the implied loss preference parameter for each individual company in every forecast type-horizon combination, thus, allowing the formation of an empirical distribution of loss preference parameters in each of the sixteen cases. Normality is rejected in twelve out of sixteen cases, particularly due to the presence of skewness. For all types of forecasts we observe statistically significant differences across the distributions of different forecast horizons, documenting heterogeneity of forecast preferences in which an asymmetric optimism is emerging as the forecast horizon becomes more distant.

This paper's contribution to the analyst forecast literature is threefold. First, we apply direct loss function estimation and inference procedures for first time in the earnings literature and demonstrate empirically that the analysts' loss function is asymmetric, thus justifying the observation by Lambert (2004) that there are no economic models suggesting that the loss function of analysts should be symmetric, let alone linear. We show that an important parameter in understanding an analyst's forecast bias is the degree of asymmetric loss and not the linearity of the loss function, i.e. linear vs. quadratic. Indeed, the asymmetry exists whether we test it on a piecewise linear (i.e. Lin-Lin model) or quadratic (i.e. Quad-Quad model) loss function. It is also present in different choices of forecast type, such as mean and median quarterly consensus or even the maximum and minimum values used to calculate the consensus. Our results cast doubts to the conclusions of Gu and Wu (2003) and Basu and Markov (2004) but, overall, are supportive of the literature claiming that there are rational, economic incentives behind the observed forecast biases.

Second, we show that the entire distribution of forecast error loss preferences changes with the forecast horizon. For example, focusing on the mean of the distributions, we observe the average level of asymmetry to increase monotonically with the forecasting horizon. This shows that the cost of providing a negative (positive) forecast error, therefore an optimistic (pessimistic) forecast when the error is defined as actual minus forecasted earnings, decreases (increases) as we move from one-quarter forecasts to four-quarter forecasts. This is consistent with empirical findings that analysts are more prudent when providing short-horizon forecasts and become more optimistic for longer-horizon forecasts. In particular, it confirms the "walk-down" phenomenon as reported in Richardson *et al.* (1999), but unlike Richardson *et al.* (2004) we show that this phenomenon can be explained through analysts' -not managerial- incentives.

Third, we implement a testing procedure to assess the rationality of forecasts in all types and horizons. In particular, we test the joint null hypothesis of forecast optimality and loss asymmetry, and find that it cannot be rejected for short horizons whilst the rate of rejection increases for distant forecasts. The latter results indicate that, although asymmetric loss is present, the full understanding of forecast optimality would need to develop further sophistication on the subject.

The rest of the paper is organized as follows: Section 2 provides a brief review of the analyst forecasts literature; section 3 explains the methodology applied in this paper. In section 4 we report our results and in section 5 we provide tests of forecast rationality. Finally in section 6 we discuss certain implications as well as limitations of this study and in section 7 we conclude.

## 2. Reviewing the Literature on Earnings Forecast Preferences

Analysts' earnings forecasts are an important source of information for investors attempting to price a firm. Therefore, any systematic errors in the forecasts could lead investors to firm mis-valuation. The extensive literature on analyst forecasts reports on average an optimistic bias (for a review see Kothari, 2001). Some researchers argue that this bias is rational since it stems from economic incentives (Dugar and Nathan, 1995; Lin and McNichols, 1998; Lim, 2001; Gu and Wu, 2003; Basu and Markov, 2004). Others claim that the bias is driven by irrational behaviour, i.e. cognitive bias, when analysts overreact asymmetrically to good and bad information about earnings (Elton *et al.*, 1984; DeBondt and Thaler, 1990; DeBondt, 1992). None of the above approaches estimates directly the loss preference parameters and in this sense they are indirect. By utilizing the recent direct estimation and inference method of Elliott et al (2005), this paper provides an empirical framework for the assessment of the existing approaches.

Understanding the source of the apparent bias by analysts has been the focus of the literature on both consensus and individual forecasts for some time now. A well documented result identifies affiliated analysts, i.e. analysts that work for investment-banking firms that offer corporate finance services to the targeted companies, as the more likely ones to provide optimistic forecasts about the targets (see Dugar and Nathan, 1995; Lin and McNichols, 1998). The rationale behind this result lies in the pecuniary incentives the investment banks have in keeping the management team of the targeted firm happy, which on a trade-off basis could overcome the costs associated with the damage in the analysts' reputation caused by the forecast error. In addition, Jackson (2005) shows that forecast optimism can exist even after removing investment-banking affiliations, since investment-banking incentives could be replaced by trade-generation incentives, therefore keeping the above mentioned trade-off intact. Lim (2001) identifies analysts that operate under conditions of substantial information asymmetry with a firm's management team as the source of the optimistic bias. He claims that the analysts' optimism allows them to build better relations with the management team therefore reducing the information asymmetry and improving forecast accuracy in the long run. This argument also informs the research design of Libby *et al.* (2007).

Recent empirical evidence though suggests that the optimistic bias exists only for long forecasting horizons, with short horizon forecasts turning pessimistic especially in recent years (Richardson *et al.*, 1999; Matsumoto, 2002; Richardson *et al.*, 2004). The explanation of this trend can be based on an earnings-guidance game, in which managers through the use of discretionary information influence analysts to lower their forecasted earnings targets shortly before the announcement, so as for the firms to avoid negative earnings surprises. Meeting earnings expectations would result in significantly greater abnormal annual returns for the firm, (Kasznik and McNichols, 2002). In other words, the capital markets reward the companies that beat analysts' expectations by offering them higher market valuations. According to Richardson *et al.* (2004) recent institutional and regulatory changes have increased the managerial incentives to guide and beat analyst expectations. These incentives relate to either private managerial benefits, i.e. sale of managerial shareholdings or the exercise of executive stock options, or firm level benefits, i.e. new equity issues.

In contrast, recent papers by Gu and Wu (2003), Basu and Markov (2004) and Clatworthy *et al.* (2006) try to explain the observed bias through an indirect use of the characteristics of the analysts' loss functions. Gu and Wu (2003) argue that analysts have linear loss functions since they care more about minimising the mean absolute forecast error instead of the squared one, which would imply a quadratic loss function. They claim that since there is a well documented presence of right skewness in the earnings distribution, it is the median of the distribution that will minimise the error and not the mean: *"When analysts forecast the median earnings on one hand, and forecast bias is measured by the mean deviation of earnings from the forecast on the other hand, the forecast bias is simply the mean–median difference of the earnings distribution"* (p. 6). Basu and Markov (2004) also analyse the forecast bias along these lines. Instead of using OLS regressions they use least absolute deviation (LAD) ones and find that the estimated coefficients are very close to their predicted values. They conclude that after assuming a linear loss function there is virtually no evidence of forecast inefficiency. Finally, Clatworthy *et al.* (2006) show that not only the skewness but also the variance of the forecast error distribution is a significant determinant of the forecast error. They illustrate that the result is robust even across portfolios formed on the basis of firm characteristics, such as book-to-price ratio and market capitalization. After assuming a Linex loss function they interpret this result as evidence of asymmetric loss.

## 3. Loss Function Estimation and Testing

The theory of optimal forecasting has been advanced significantly over the last three decades. Granger (1969) first relaxed the assumption of symmetric loss preferences and considered the formation of optimal forecasts under asymmetric loss functions. Since then, a number of different loss function specifications have been proposed, including the linear-exponential (LinEx) of Varian (1974) and Zellner (1986), the double linear (Lin-Lin) and the double quadratic (Quad-Quad), see Granger (1999) for a review. Christofersen and Diebold (1997) considered optimal forecasting under asymmetric loss and conditional heteroscedasticity and Christodoulakis (2005, 2006) considered the interaction between preference and distribution asymmetries. In spite of the progress in forecast theory, the form and the parameters of the underlying loss function were always considered as unknown in the literature, which developed a number of indirect approaches to assess the presence of forecast bias and asymmetric loss preferences as explained in the previous section. Batchelor and Peel (1998) provided the first specific approach to estimate the parameter of a LinEx loss function in the context of an augmented Mincer-Zarnowitz regression of forecast errors in the presence of ARCH-in-Mean effects.

A general approach to the estimation of the parameter of a loss function has recently been proposed by Elliott et al. (2005) and further studied by Christodoulakis and Mamatzakis (2008). The method is based on Generalized Method of Moments type of arguments and we shall follow this paradigm in our empirical work. For the benefit of the reader we shall outline the method in brief, following the notation of the original paper. We shall consider a flexible loss function of the form:

$$L(p,a) \equiv [a + (1-2a)\mathbf{1}_{(Y_{t+1}-f_{t+1}<0)}]\left|Y_{t+1} - f_{t+1}\right|^{p} \tag{1}$$

where, $Y_{t+1} - f_{t+1}$ denotes the forecast error, parameter $p$ = 1,2, parameter $a \in (0,1)$ and **1** is a unit indicator if $Y_{t+1} - f_{t+1} < 0$ and zero otherwise. For $p$ = 1 the function is the double linear (Lin-Lin) loss and for $p$ = 2 it is the double quadratic (Quad-Quad) loss. In the context of earnings forecasts and irrespective of the value of $p$, for $\alpha$ < 0.5 ($\alpha$ > 0.5) the loss assigns higher penalty to negative (positive) forecast errors, that is over-predictions (under-predictions) of earnings and for $\alpha$ = 0.5 the loss penalises symmetrically positive and negative forecast errors.

The method assumes that a sequence of forecast errors $\{Y_{t+1} - f_{t+1}\}$, with $\tau \le t < T + \tau$, is observable together with a $d$ x 1 vector $\boldsymbol{v}_t$ of instruments which is a subset of the full information set $\boldsymbol{W}_t$ used to generate the forecast $f$. Then an estimate for $\alpha$ is constructed using a linear Instrumental Variable estimator $\hat{a}_T$, as follows:

$$\hat{a}_T = \frac{\left[\frac{1}{\mathrm{T}}\sum_{t=\tau}^{\mathrm{T}+\tau-1} \mathbf{v}_t |Y_{t+1} - f_{t+1}|^{p-1}\right]' \hat{S}^{-1} \left[\frac{1}{\mathrm{T}}\sum_{t=\tau}^{\mathrm{T}+\tau-1} \mathbf{v}_t \mathbf{1}_{(Y_{t+1} - f_{t+1} < 0)} |Y_{t+1} - f_{t+1}|^{p-1}\right]}{\left[\frac{1}{\mathrm{T}}\sum_{t=\tau}^{\mathrm{T}+\tau-1} \mathbf{v}_t |Y_{t+1} - f_{t+1}|^{p-1}\right]' \hat{S}^{-1} \left[\frac{1}{\mathrm{T}}\sum_{t=\tau}^{\mathrm{T}+\tau-1} \mathbf{v}_t |Y_{t+1} - f_{t+1}|^{p-1}\right]} \tag{2}$$

and $\hat{S}$ is given by:

$$\hat{S} = \frac{1}{\mathrm{T}}\sum_{t=\tau}^{\mathrm{T}+\tau-1} \mathbf{v}_t \mathbf{v}_t' (\mathbf{1}_{(Y_{t+1} - f_{t+1} < 0)} - \hat{a}_T)^2 |Y_{t+1} - f_{t+1}|^{2p-2} \tag{3}$$

To make equation (2) implementable, since $\hat{S}$ depends on $\hat{a}_T$, estimation is performed iteratively, assuming $S = I$ in the first iteration to estimate $\hat{a}_{T,1}$, until convergence. Elliott et al (2005) show that the estimator of $\hat{a}_T$ is asymptotically normal and thus testing procedures are readily available since $T^{\frac{1}{2}}(\hat{a}_T - a_0) \xrightarrow{d} N\left(0, \left(h' S^{-1} h\right)^{-1}\right)$, where $S$ is the population counterpart of equation (3) and $h \equiv E\left[\mathbf{v}_t |Y_{t+1} - f_{t+1}|^{p-1}\right]$ . To promote robustness in our empirical analysis, we consider $p = 1$ and $p = 2$, using two instruments, in particular a constant and the lagged forecast error of earnings. In the context of asymmetric preferences given in equation (1), $f_{t+1}$ is an optimal forecast satisfying the first order optimality conditions

$$E\left[W_t \left(\mathbf{1}_{(Y_{t+1} - f_{t+1} < 0)} - a\right) |Y_{t+1} - f_{t+1}|^{p-1}\right] = 0 \tag{4}$$

Since for given $a$ and $p$ the forecaster uses the above condition to uniquely determine $f_{t+1}$, then for given $f_{t+1}$ and the respective realization, it is possible to use the same condition to uniquely back out $a$ using equations (2) and (3).

## 4. Data Sets and Empirical Results

Our sample comprises of US firms over the period of 1983 to 2006 covered by I/B/E/S. For each quarterly earnings of a firm we extract 4 types of analyst forecasts errors, i.e. mean consensus, median consensus, highest, and lowest, over 4 forecast horizons, i.e. 1 to 4 quarters ahead. Forecast error is defined as actual less forecasted earnings, so negative value implies optimism. Because of the asymptotic nature of the Elliott al (2005) method, we have restricted our analysis to all those companies that can provide a time series of at least 50 forecast observations along with the respective earnings realization. Thus, the final number of companies we apply in our study are 1734, 1391, 1131, and 791 for 1, 2, 3, and 4-quarter horizon analyst forecasts respectively. Thus, for every company we form 16 (4 × 4) distinct time series of quarterly frequency forecast errors, corresponding to different forecast type vs. horizon combinations. Table 1 presents the descriptive statistics of our sample. For each time series, we estimate the loss function parameter, $\alpha$, of equation (1) using the Elliott et al method described by equations (2) and (3), both for double linear ( $p = 1$) and double quadratic ($p = 2$) loss functions.

For the case of the double linear loss function, we depict the empirical distribution of coefficient $\alpha$ in each of our sixteen samples in figures 1-16. In Table 2 we present the associated statistics up to the forth order and the Jarque-Bera non-normality test. To interpret our results, recall that a loss parameter $\alpha < 0.5$ ($\alpha > 0.5$) implies preference that penalises more heavily negative (positive) forecast errors, i.e. over-predictions (under-predictions). Thus, $\alpha < 0.5$ can be associated with conservative or pessimistic preferences, $\alpha > 0.5$ with optimistic preferences and $\alpha = 0.5$ with symmetric or neutral preferences. Turning our attention to the estimated average of the sixteen distributions of estimated $\alpha$ parameters, we observe that the average $\alpha$ for all four types of forecasts is increasing as the forecast horizon increases. The behaviour for mean and median forecasts is similar and the average preferences are shown to be conservative for one-quarter horizon, neutral for two-quarter horizon and then turn to optimistic for three- and four-quarter horizons. The average parameters for maximum (minimum) forecasts indicate optimistic (pessimistic) preferences for all horizons and the degree of optimism (pessimism) is increasing (decreasing) for longer horizons. Furthermore, the standard deviation is also increasing with the forecast horizon for all four types of forecast, indicating a tendency for the preferences to disperse more as the forecasting target becomes more distant.

It is now interesting to examine the degree of asymmetry of our sixteen empirical distributions and how these evolve for longer forecast horizons. From Table 2 we observe that for preferences of mean and median forecasts, skewness is decreasing as forecast horizon becomes more distant. It is positive for the first two forecast horizons, indicating higher chances to observe preferences to the right of the mean, i.e. neutral or optimistic. Then it turns to negative, indicating higher chances to observe preferences to the left of the mean, i.e. neutral or pessimistic. In contrast, the estimated kurtosis is relatively stable across all samples with slight deviations from the normal value of three. Inspecting the estimates of the Jarque-Bera non-normality tests, we observe that normality is rejected in all cases except four in which skewness is close to zero.

Given the symmetric nature of standard deviation and kurtosis, the joint examination of the mean and skewness estimates suggests that they tend to move to the opposite direction as the forecast horizon becomes more distant. When the general tendency of the market is towards pessimism (optimism), there is a high concentration above (below) the mean and a wide dispersion below (above) the mean. This requires a modest majority of earnings forecasters to move towards optimism at every step forward. These findings are robust for all four types of forecasts.

Although each individual parameter estimate from equations (2) and (3) is statistically significant, it is indispensable to examine whether such term-structure properties of the empirical distributions are significant or due to chance. In Table 3 we present our estimates of the Kolmogorov-Smirnov test for the difference between two empirical distributions of different forecast horizons. For all types of forecasts we report strong evidence of statistically significant distributional differences for forecast preferences across horizons. One exception concerns median forecasts for three- and four-quarters horizon. Finally, we run the same analysis for a double quadratic loss function ($p = 2$) and obtained results that are qualitatively the same with linear loss although our estimates now take higher values due to the quadratic nature of the loss function, we do not report our findings in the paper for reasons of space but they are available to the reader upon request.

### 5. Tests of Forecast Rationality

Our Generalised Method of Moments estimation method involves two instruments, a constant and the lagged forecast error of earnings as a conditioning set to estimate the alpha parameter that optimizes the loss function. In this context it is possible to test the joint null hypothesis of forecast optimality and loss asymmetry. For this purpose, Elliott et al (2005) offer a J-test for overidentification which is shown to follow a Chi-Square distribution with degrees of freedom equal to the number of instruments minus one. This takes the form

$$J = \frac{1}{\mathrm{T}} \left[ \begin{array}{l} \left( \sum_{t=\tau}^{\mathrm{T}+\tau-1} \mathbf{v}_t \left[ \mathbf{1}_{(Y_{t+1} - f_{t+1} < 0)} - \hat{a}_T ) \right] \left| Y_{t+1} - f_{t+1} \right|^{p-1} \right)' \hat{S}^{-1} \\ \cdot \left( \sum_{t=\tau}^{\mathrm{T}+\tau-1} \mathbf{v}_t \left[ \mathbf{1}_{(Y_{t+1} - f_{t+1} < 0)} - \hat{a}_T ) \right] \left| Y_{t+1} - f_{t+1} \right|^{p-1} \right) \end{array} \right] \sim \chi^2_{d-1}$$

We have calculated the J-statistic for each individual estimated alpha coefficient and all forecast types across all horizons and present our estimates in Figures 17, 21, 25 and 29. Furthermore, we calculated the associated J-statistics for the imposed hypotheses of alpha being equal to 0.2 (Figures 18, 22, 26 and 30), 0.5 (Figures 19, 23, 27 and 31) and 0.8 (Figures 20, 24 and 28 and 32). Our results suggest that under the imposed hypotheses of alpha coefficient being equal to 0.2, 0.5 or 0.8, we observe extensive rejection of the joint null hypothesis of forecast optimality and the imposed value of alpha for all forecast horizons. Naturally, the degree of the rejection is larger for some forecast types, e.g. in Figure 18 we observe that the joint null of forecast optimality and $\alpha = 0.2$ is massively rejected in the case of maximum forecasts, massively accepted for minimum forecasts and with mixed results for mean and median forecasts. When we test for the joint null of forecast optimality and the estimated alpha coefficient (Figures 17, 21, 25 and 29), we observe a reduction in the number of rejections of this hypothesis, which is massive for the cases of one- and two-quarter horizon but less pronounced for longer horizons. These results show that although statistically significant loss asymmetry parameters are extensively present in all forecast horizons, they suffice accept the joint null primarily for short horizons and less for longer horizons. An initial thought for the justification of these results would question the validity of the J-statistic in that it might be oversized. However, Monte Carlo results in Elliott et al (2005) under normality and in Christodoulakis and Mamatzakis (2008) under skew-normality suggest that the size of the J-statistic is remarkably well controlled. Thus, the latter suggests that the study of forecast optimality for longer horizons, such as three and four quarters, requires the development of properties that may go beyond the shape of the loss function.

## 6. Discussion

The observed asymmetry in the analysts' loss functions and the significant differences in the analysts' costs for different forecasting horizons, help explain the observed forecast biases but at the same time create a new question: why do analysts have asymmetric loss functions? There are several possible answers to this question but all of them are difficult to test. Below we offer a list of answers, as well as the problems associated with testing them.

The first possible explanation, but in our opinion the weakest, stems from the behavioural literature on forecasting. As explained in previous sections, this strand of literature attributes the forecast bias to the analysts' asymmetric overreaction to the announcement of good and bad news. In our paper, we find an asymmetry in the analysts' perceived costs associated with providing inaccurate forecasts, i.e. asymmetry in the loss function for positive vs. negative errors, which one might argue that stems from the analysts' irrational behavior. This explanation though is hard to reconcile with the fact that we also observe the "walk-down" phenomenon, where analysts appear to become more prudent as the forecast horizon shortens, i.e. optimistic for long forecast horizons, turning pessimistic for short forecast horizons. There is no theoretical prediction that the analysts' overreaction/irrationality will change in a certain, monotonic, way across different forecasting horizons. Therefore this explanation appears to be weak.

An alternative explanation is based on rational behavior on behalf of analysts and in particular on their economic incentives. As mentioned in section 2, the extensive literature in the analyst forecast area has already reported the existence of a trade-off between reputational costs and pecuniary benefits resulting from providing inaccurate forecasts. There is no prediction that these incentives reflect symmetrically on the analysts' loss functions or indeed that their effect remains constant through time. For example, it might be plausible to assume that on average the reputational costs increase for short forecast horizons, e.g. one-quarter forecasts, since it is harder for analysts to blame any forecast errors to unanticipated factors, i.e. their forecasting ability for short periods is expected to be greater. If these costs outweigh the effect of the pecuniary benefits, the result will be more prudent forecasts. Testing this plausible explanation of the asymmetry in the analysts' loss functions is not easy in our setting. Our measure of the asymmetry, alpha (α), is estimated using GMM arguments and because of the asymptotic nature of the method is based on at least 50 quarterly observations. A multivariate study of the alphas on firm-specific and macroeconomic characteristics becomes possibly of limited use since it has to be based on noisy, aggregate proxies for these characteristics. An alternative approach would be to regress the alphas on the moments, e.g. variance and skewness, of the earnings and/or returns distributions. This could possibly provide more details on the factors that mostly affect the asymmetry.

Finally, the papers by Abarbanell and Lehavy (2003) and Helbok and Walker (2004) can provide an additional interpretation of our results. Abarbanell and Lehavy (2003) argue that it is important to understand the kind of earnings the analysts attempt to forecast at any given time, since that can change depending on the firm's reporting choices. They report a link between the recognition of unexpected accruals and asymmetries in the distributions of forecasting errors, thus claiming that the forecast biases can be induced by reporting policies. Following this line of argument, Helbok and Walker (2004) find that accounting conservatism creates left skewness to the distribution of the earnings surprises, therefore is related to the observed forecast bias. They show, both theoretically and empirically, that analysts initially issue forecasts based on the permanent component of a firm's earnings, which they then revise throughout the year in order to take into consideration current year, transitory, items and especially the large, negative ones. This argument seems consistent with our results since it is reasonable to assume that forecasting permanent earnings items is easier and therefore less costly for the analysts, thus increasing their optimism. In contrast, forecasting current year transitory items is riskier and can prove costly for analysts, e.g. missing out a large negative transitory item could create a large error for a short horizon forecast which would result in large reputational costs for the analyst, therefore making them more prudent.

## 7. Concluding Remarks

We collect time series of forecast errors for the full I/B/E/S database of US companies with at least 50 quarterly observations, and estimate the parameter of the implicit loss function in sixteen cases for each company: four different forecast types across four different forecast horizons. Our analysis produced a massive quantitative output which we collect our results in the form of cross sectional empirical distributions of loss preference parameters for each of the sixteen forecast type vs. horizon combinations. Normality is rejected in twelve out of sixteen cases, particularly due to the presence of skewness. For all types of forecasts we observe statistically significant differences across the distributions of different forecast horizons. These findings document a heterogeneity of forecast loss preferences across forecast horizons which is consistent with the "walk-down" empirical stylized fact of being on average optimistic for long-run predictions but pessimistic for short-run ones. Furthermore, we performed tests of the joint null hypothesis of forecast optimality and asymmetric preferences, suggesting that forecast rationality is largely present in short horizons but is less pronounced in longer horizons.

Our results in this paper provide us with the motivation to answer the remaining questions of linking the presence of asymmetric preferences to economic incentives and fundamentals as well as of characterising forecast rationality in longer horizons. We hope to be able to address these issues in future research.

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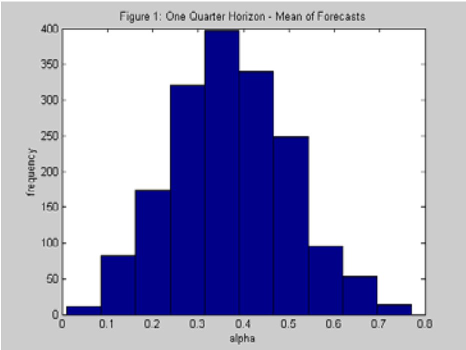
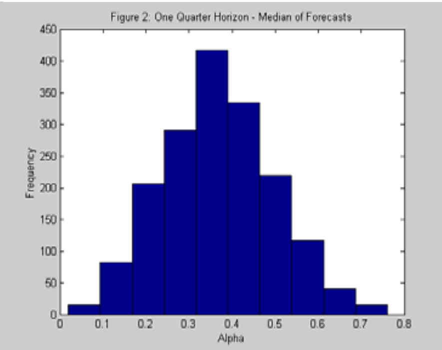
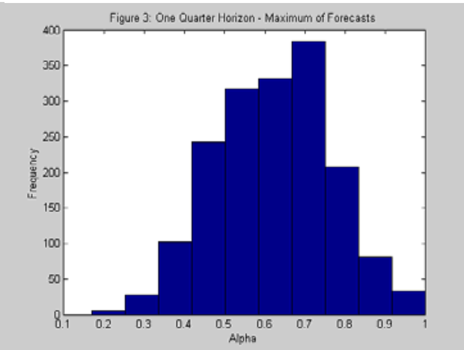
Zellner, A, (1986), Bayesian Estimation and Prediction Using Asymmetric Loss Functions, *Journal of the American Statistical Association*, Vol. 81, No. 394. (Jun., 1986), pp. 446-451.

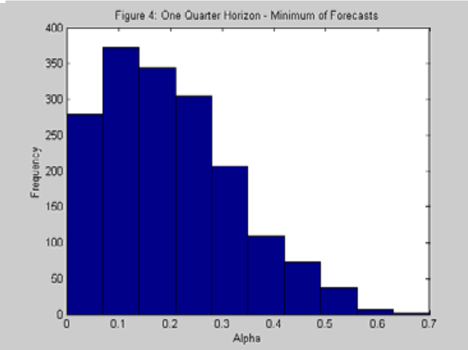
Figures 1-16. The distributions of Alpha ($\alpha$) for the 16 (4x4) combinations of different forecast types vs. forecast horizons.

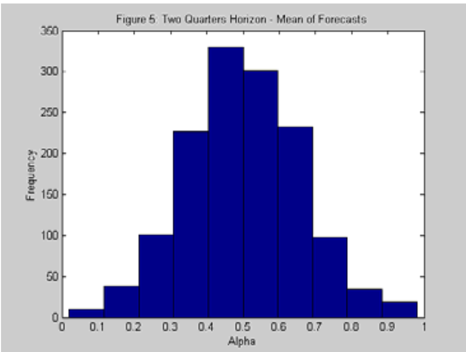
Each row of figures shows the distributions of alphas for the same forecast horizon, across different forecast types. Each column shows the distributions of alphas for the same forecast type, across different forecast horizons.

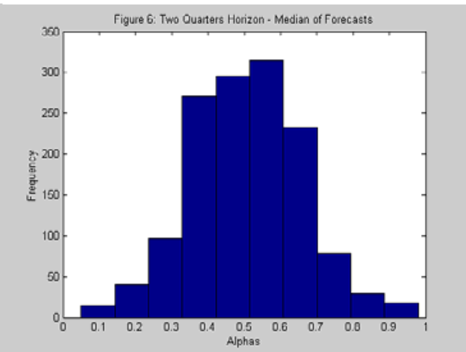


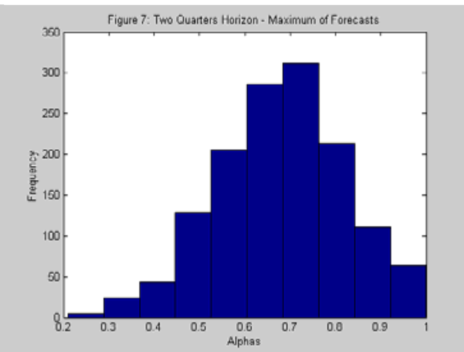



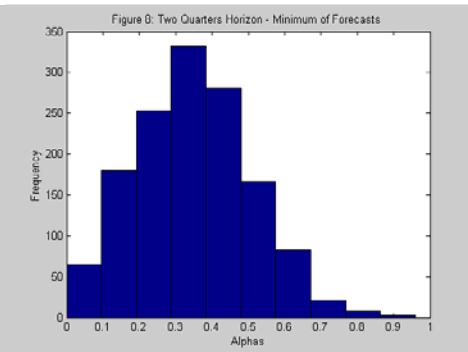

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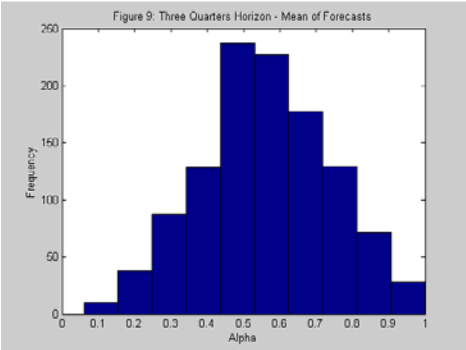


Figure 9: Three Quarters Horizon - Mean of Forecasts
Frequency
Alpha

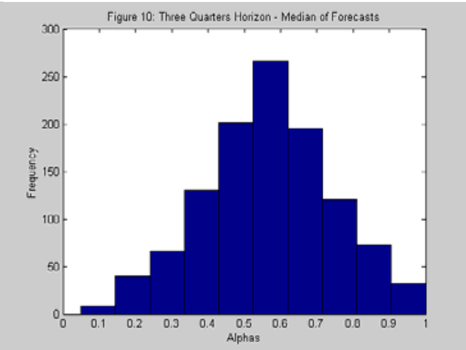


Figure 10: Three Quarters Horizon - Median of Forecasts
Frequency
Alphas

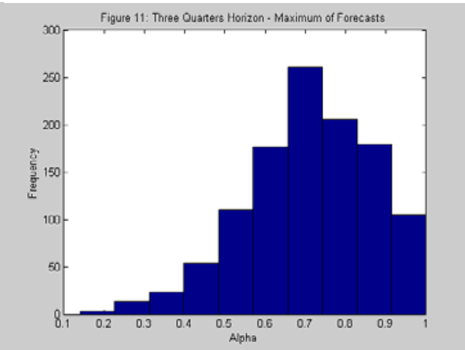


Figure 11: Three Quarters Horizon - Maximum of Forecasts
Frequency
Alpha

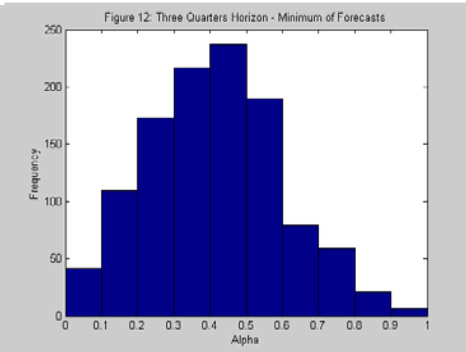


Figure 12: Three Quarters Horizon - Minimum of Forecasts
Frequency
Alpha

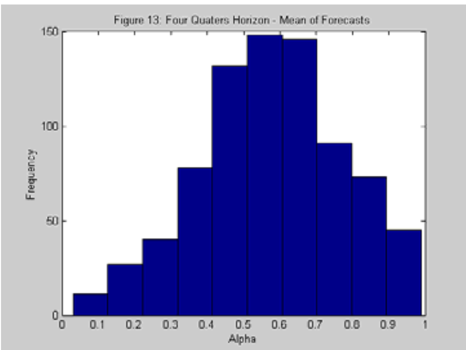


Figure 13: Four Quaters Horizon - Mean of Forecasts
Frequency
Alpha

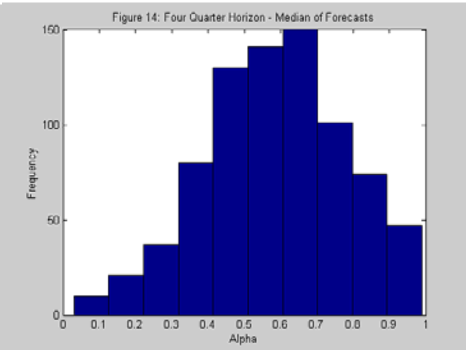


Figure 14: Four Quarter Horizon - Median of Forecasts
Frequency
Alpha

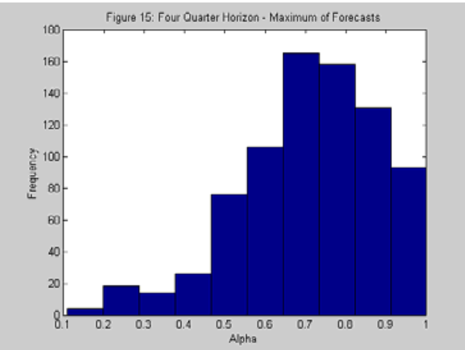


Figure 15: Four Quarter Horizon - Maximum of Forecasts
Frequency
Alpha

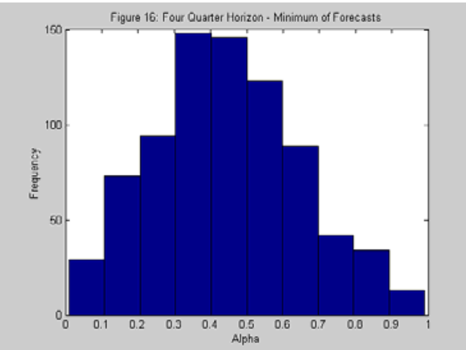
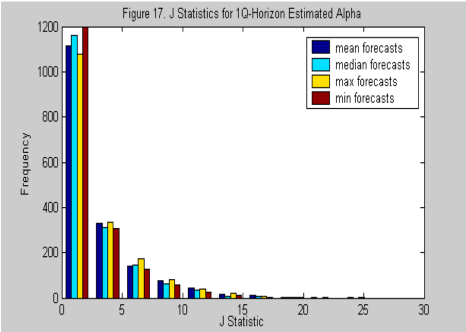
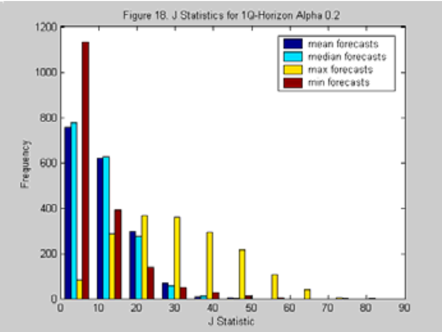


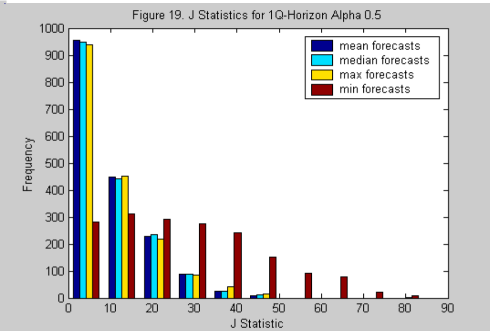
Figure 16: Four Quarter Horizon - Minimum of Forecasts
Frequency
Alpha

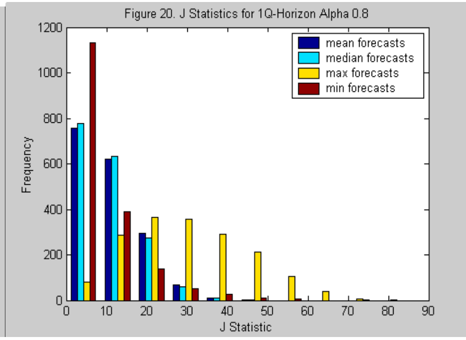
Figures 17-32. The distributions of J-Statistic for the 16 (4x4) combinations of different forecast horizons vs hypothesis for true Alpha (α).

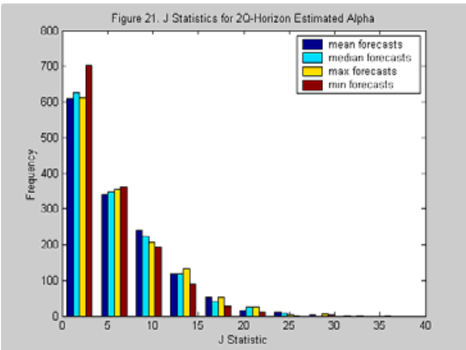
Each row of figures shows the distributions of J-Statistics for the same forecast horizon, across different hypotheses for the true alpha. Each column shows the distributions of J-Statistics for the same hypothesis of true Alpha, across different forecast horizons. Each individual figure contains distributions for four types of forecast: mean, median, maximum and minimum.

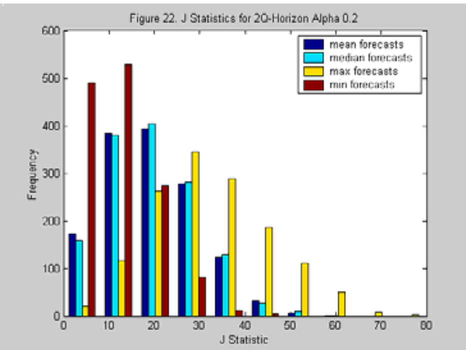


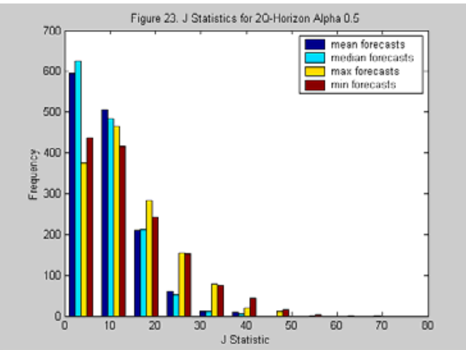



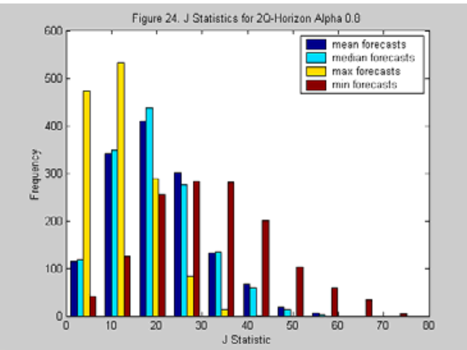



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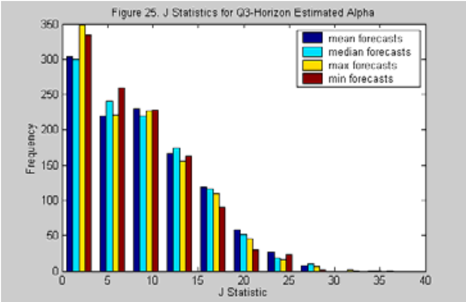

Figure 25. J Statistics for Q3-Horizon Estimated Alpha

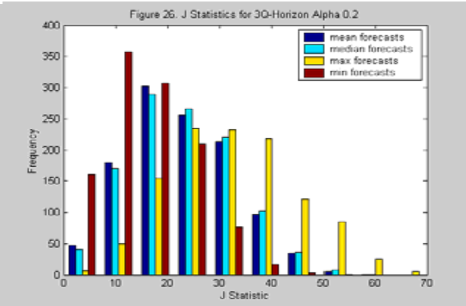

Figure 26. J Statistics for 3Q-Horizon Alpha 0.2

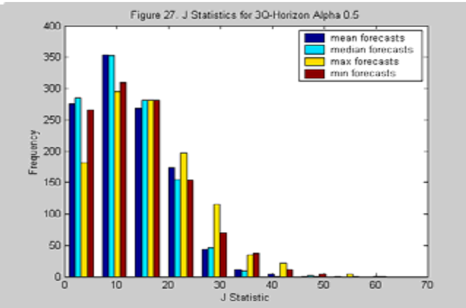

Figure 27. J Statistics for 3Q-Horizon Alpha 0.5

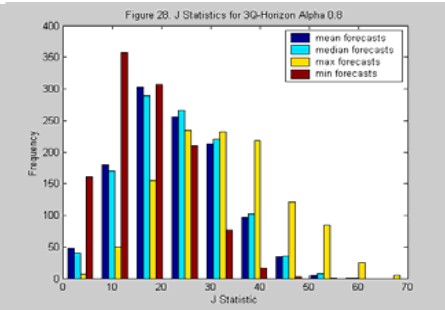

Figure 28. J Statistics for 3Q-Horizon Alpha 0.8

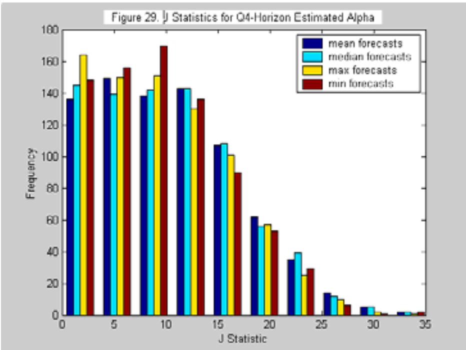

Figure 29. J Statistics for Q4-Horizon Estimated Alpha

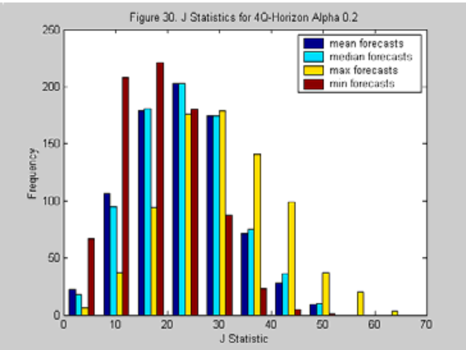

Figure 30. J Statistics for 4Q-Horizon Alpha 0.2

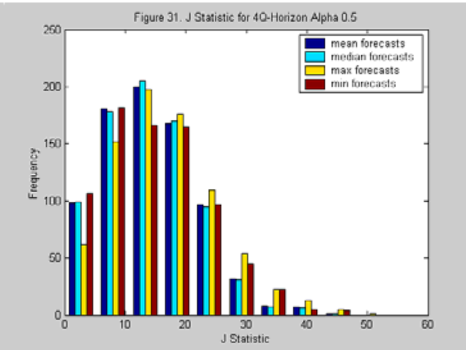

Figure 31. J Statistic for 4Q-Horizon Alpha 0.5

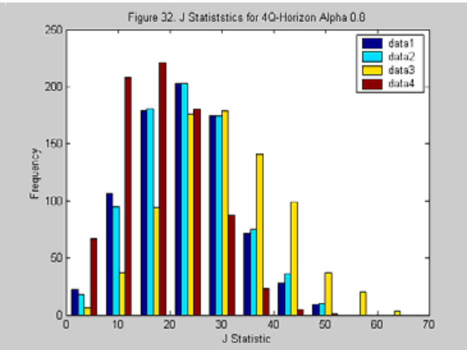

Figure 32. J Statiststics for 4Q-Horizon Alpha 0.8

**Table 1. Descriptive statistics**

| Panel A: 1 quarter | | | | | | |
|---|---|---|---|---|---|---|
| Forecast errors | Obs | Mean | Stdev | 25th | 50th | 75th |
| Mean | 122298 | -0.018 | 1.511 | -0.015 | 0.002 | 0.020 |
| Median | 122298 | -0.018 | 1.511 | -0.013 | 0.002 | 0.020 |
| Highest | 122298 | -0.062 | 1.560 | -0.050 | -0.010 | 0.006 |
| Lowest | 122298 | 0.025 | 1.525 | 0.000 | 0.017 | 0.050 |
| **Panel B: 2 quarters** | | | | | | |
| Forecast errors | Obs | Mean | Stdev | 25th | 50th | 75th |
| Mean | 94551 | -0.044 | 0.772 | -0.045 | 0.000 | 0.020 |
| Median | 94551 | -0.045 | 0.772 | -0.047 | -0.001 | 0.020 |
| Highest | 94551 | -0.082 | 0.830 | -0.075 | -0.016 | 0.007 |
| Lowest | 94551 | -0.007 | 0.765 | -0.020 | 0.010 | 0.040 |
| **Panel C: 3 quarters** | | | | | | |
| Forecast errors | Obs | Mean | Stdev | 25th | 50th | 75th |
| Mean | 75623 | -0.063 | 1.223 | -0.060 | -0.005 | 0.020 |
| Median | 75623 | -0.065 | 1.228 | -0.061 | -0.007 | 0.020 |
| Highest | 75623 | -0.099 | 1.252 | -0.090 | -0.020 | 0.008 |
| Lowest | 75623 | -0.028 | 1.208 | -0.040 | 0.003 | 0.040 |
| **Panel D: 4 quarters** | | | | | | |
| Forecast errors | Obs | Mean | Stdev | 25th | 50th | 75th |
| Mean | 50773 | -0.062 | 0.842 | -0.070 | -0.007 | 0.020 |
| Median | 50773 | -0.064 | 0.842 | -0.070 | -0.008 | 0.020 |
| Highest | 50773 | -0.096 | 0.869 | -0.100 | -0.020 | 0.010 |
| Lowest | 50773 | -0.029 | 0.855 | -0.050 | 0.001 | 0.040 |

Note: This table presents the descriptive statistics of our sample. Panels A to D shows errors of made 1 to 4 quarter ahead analyst forecasts respectively. For each quarterly earnings of a firm we measure 4 types of analyst forecasts errors, i.e. mean consensus, median consensus, highest, and lowest. Forecast error is defined as actual less forecasted earnings, so negative value implies optimism.

**Table 2. Statistics of Estimated Loss Function Parameters**

| | | Mean Forecast | Median Forecast | Maximum Forecast | Minimum Forecast |
|---|---|---|---|---|---|
| One Quarter Horizon | $\mu$ | 0.372 | 0.368 | 0.622 | 0.205 |
| | $\sigma$ | 0.129 | 0.127 | 0.144 | 0.128 |
| | *s* | 0.128 | 0.129 | -0.052 | 0.67 |
| | *k* | 2.765 | 2.770 | 2.619 | 3.068 |
| | *j-b* | 2.847 | 8.713 | 11.40 | 129 |
| | | (0.01) | (0.01) | (0.003) | (0.000) |
| Two Quarters Horizon | $\mu$ | 0.501 | 0.508 | 0.680 | 0.350 |
| | $\sigma$ | 0.158 | 0.154 | 0.142 | 0.158 |
| | *s* | 0.095 | 0.070 | -0.217 | 0.280 |
| | *k* | 3.065 | 3.203 | 2.882 | 2.963 |
| | *j-b* | 2.342 | 3.417 | 11.81 | 18.23 |
| | | (0.31) | (0.18) | (0.003) | (0.000) |
| Three Quarters Horizon | $\mu$ | 0.561 | 0.569 | 0.701 | 0.419 |
| | $\sigma$ | 0.178 | 0.176 | 0.154 | 0.184 |
| | *s* | -0.044 | -0.074 | -0.474 | 0.249 |
| | *k* | 2.671 | 2.757 | 3.073 | 2.788 |
| | *j-b* | 5.600 | 3.923 | 42.55 | 13.89 |
| | | (0.06) | (0.14) | (0.000) | (0.001) |
| Four Quarters Horizon | $\mu$ | 0.578 | 0.587 | 0.711 | 0.447 |
| | $\sigma$ | 0.197 | 0.193 | 0.172 | 0.200 |
| | *s* | -0.172 | -0.218 | -0.670 | 0.226 |
| | *k* | 2.593 | 2.694 | 3.267 | 2.633 |
| | *j-b* | 9.52 | 9.45 | 61.31 | 11.34 |
| | | (0.009) | (0.009) | (0.000) | (0.003) |

Note: ***μ***, ***σ, s, k, j-b*** denote mean, standard deviation, skewness, kurtosis and the Jarque-Bera test respectively. P-values in brackets.

**Table 3: Kolmogorov-Smirnov Tests**

**Panel A: Kolmogorov-Smirnov Tests for Mean Forecasts**

| | One Quarter Horizon | Two Quarters Horizon | Three Quarters Horizon | Four Quarters Horizon |
|---|---|---|---|---|
| One Quarter Horizon | - | 0.35<br>(0.00) | 0.48<br>(0.00) | 0.51<br>(0.00) |
| Two Quarters Horizon | - | - | 0.15<br>(0.00) | 0.21<br>(0.00) |
| Three Quarters Horizon | - | - | - | 0.064<br>(0.04) |
| Four Quarters Horizon | - | - | - | - |

**Panel B: Kolmogorov-Smirnov Tests for Median Forecasts**

| | One Quarter Horizon | Two Quarters Horizon | Three Quarters Horizon | Four Quarters Horizon |
|---|---|---|---|---|
| One Quarter Horizon | - | 0.39<br>(0.00) | 0.52<br>(0.00) | 0.54<br>(0.00) |
| Two Quarters Horizon | - | - | 0.18<br>(0.00) | 0.22<br>(0.00) |
| Three Quarters Horizon | - | - | - | 0.07<br>(0.01) |
| Four Quarters Horizon | - | - | - | - |

**Panel C: Kolmogorov-Smirnov Tests for Maximum Forecasts**

| | One Quarter Horizon | Two Quarters Horizon | Three Quarters Horizon | Four Quarters Horizon |
|---|---|---|---|---|
| One Quarter Horizon | - | 0.17<br>(0.00) | 2.5<br>(0.00) | 2.6<br>(0.00) |
| Two Quarters Horizon | - | - | 0.11 | 0.14<br>(0.00) |
| Three Quarters Horizon | - | - | - | 0.04<br>(0.38) |
| Four Quarters Horizon | - | - | - | - |

**Panel D: Kolmogorov-Smirnov Tests for Minimum Forecasts**

| | One Quarter Horizon | Two Quarters Horizon | Three Quarters Horizon | Four Quarters Horizon |
|---|---|---|---|---|
| One Quarter Horizon | - | 0.41<br>(0.00) | 0.51<br>(0.00) | 0.54<br>(0.00) |
| Two Quarters Horizon | - | - | 0.17<br>(0.00) | 0.23<br>(0.00) |
| Three Quarters Horizon | - | - | - | 0.07<br>(0.01) |
| Four Quarters Horizon | - | - | - | - |

P-values in brackets