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Are Analysts' Loss Functions Asymmetric?

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1. Introduction

Financial analysts' forecasts of corporate earnings are an important input to investors' decision models, e.g. valuation models. Yet there is extensive evidence suggesting that analysts' forecasts are "irrational" – specifically they appear to be biased (ex post forecast errors have a non-zero mean) and inefficient (ex post forecast errors are correlated with information known at the forecast date).[1] Recent work has proposed two explanations for such findings based on the idea that the statistical bias and inefficiency of forecasts is rational and originates in the loss functions underpinning analysts' forecast decisions, i.e. how analysts weight prospective prediction errors when deciding on "optimal" earnings forecasts. For example, Gu and Wu (2003) and Basu and Markov (2004) suggest that analysts have linear loss functions. A mutually exclusive alternative explanation is that analysts have asymmetric loss functions, perhaps motivated by private incentives originating in business relationships between securities firms and their investment banking clients, or in analysts' dependence on managers for information (e.g. Lin and McNichols, 1998; Dugar and Nathan, 1995; Lim, 2001; Hong and Kubik, 2003).[2] Prior research reports evidence consistent with both explanations, but does not test the linear loss explanation against the asymmetric loss alternative. Better understanding of the nature of analysts' loss functions is potentially important for investors. Although it is investors' loss functions which ultimately determine investment decisions, interpretation and use of analysts' forecasts by investors should reflect beliefs concerning analysts' loss functions (Lambert, 2004, p.221). This paper contains new evidence suggesting analysts' earnings forecasts are driven by asymmetric loss functions.

[1] See Kothari (2001) for a review.
[2] Other explanations forecast bias and inefficiency proposed in the literature suggest either that analysts are irrational and display cognitive biases (e.g. Friesen and Weller, 2002), or that there are incentives for them to report forecasts untruthfully or selectively (e.g. McNichols and O'Brien, 1998).

Understanding the nature of analysts' loss functions is relevant to interpreting and using forecasts because a rational analyst's "optimal" earnings forecast depends on both the subjective probability distribution of earnings and on the analyst's loss function. A rational analyst with a quadratic loss function minimizes the mean squared value of anticipated forecast errors (MSE), and in this case the optimal forecast is the conditional mean of earnings and the expected value of the mean forecast error is zero; however, the median forecast error depends on the distribution of earnings. In contrast, a rational analyst with a symmetric linear loss function minimizes the mean absolute value of anticipated forecast errors (MAE), the optimal forecast is the conditional median and the expected value of the median forecast error is zero, while the mean value depends on the distribution of earnings. Similar to a quadratic loss function, a linear loss function is symmetric in weighting positive and negative forecast errors of the same magnitude, but it gives less weight to extreme forecast errors.[3] In the case of asymmetric loss functions, optimal forecasts are not consistent with the MSE or MAE criteria and both mean and median forecast errors can have expected values different from zero (Keane and Runkle, 1998). The properties of forecast errors under asymmetric loss depend on both the distribution of earnings and on the functional form and parameters of the loss function.

We test whether analysts produce forecasts consistent with asymmetric loss functions against the alternative of symmetric loss (either quadratic or linear). Our analysis is based on theoretical predictions relating forecast errors to the variance and skewness of the forecast error distribution. Our approach builds on Gu and Wu (2003), who conjecture that, due to analysts facing linear loss functions, the magnitude of forecast errors depends on ex ante skewness of the earnings (and hence of forecast error) distribution, though not on the variance. Consistent with this prediction, Gu and Wu (2003) report evidence that forecast errors are positively associated with the skewness of earnings, although they do not control for variance. Our analysis of asymmetric loss assumes that analysts' loss functions belong to the Linex class of asymmetric loss functions introduced by Varian (1974) and Zellner (1986). Under Linex loss functions,

[3] Granger (1969) proposes a piecewise linear (LIN-LIN) loss function that weights positive and negative forecast errors of similar magnitude differently.

forecast errors are predicted to depend on the *variance* of the forecast error. If the distribution of forecast errors is conditionally non-normal, forecast errors under Linex loss functions also depend on higher moments, including skewness. The linear (MAE) loss function is a special limiting case in which forecast errors depend only on skewness. Dependence of forecast errors on the forecast error variance under Linex-class asymmetric loss functions but not under linear loss functions suggests a way of discriminating between symmetric linear and asymmetric loss functions.

We test whether the ex ante variance of the forecast error is incrementally significant in a regression that includes both variance and skewness instruments. Our results confirm that the ex ante forecast error variance instrument is a significant determinant of the forecast error. This is consistent with financial analysts having asymmetric loss functions. Further analysis reveals that the dominant role of forecast error variance in explaining forecast bias is robust across portfolios formed on the basis of book-to-price ratio and market capitalization. These firm characteristics are known determinants of forecast error accuracy and skewness.

The rest of the paper is organized as follows. In section 2, we discuss the theory of the Linex loss function and derive empirical predictions that distinguish between linear and asymmetric loss. In section 3 we describe our empirical research design. In section 4 we describe our dataset and report our empirical results. Section 5 contains our conclusions.

2. Loss functions and forecast bias

Two elements of the forecasting process determine whether a rational earnings forecast is biased. The analyst's loss function and the subjective probability distribution associated with the variable being forecasted combine to generate an optimal forecast. If the subjective probability distribution of earnings is skewed, rational forecasts produced by analysts with symmetric loss functions will be biased, unless the loss function is quadratic (Gu and Wu, 2003; Basu and Markov, 2004). However, earnings skewness is not *necessary* for optimal forecasts to be biased because of the role played by the loss function. Although Christofferson and Diebold (1997) show that closed form solutions for the optimal forecast cannot be developed for general asymmetric loss functions, the properties of optimal forecasts have been analyzed for two specific asymmetric loss functions: Lin-Lin and Linex.

Granger (1969) demonstrates that even if the data generating process for a variable follows an *unconditional* Gaussian process, optimal forecasts will exhibit constant bias when the forecaster optimizes with reference to an asymmetric, piecewise-linear, Lin-Lin loss function. In this case the constant marginal loss (or cost) associated a unit forecast error above some threshold (e.g. zero) is different from the constant marginal loss for a unit forecast error below the threshold. The magnitude of the optimal bias depends on the parameters of the loss function, and on the forecast error variance. Christofferson and Diebold (1996, 1997) extend Granger's analysis to *conditional* Gaussian processes. In this case, optimal forecasts exhibit *time-varying* bias, conditional on the time-varying forecast error variance.

The Linex loss function is a more general asymmetric loss function specification than Lin-Lin (Varian, 1974; Zellner, 1986). Assume that the variable to be forecast is earnings at time *t*, denoted y_t. The Linex loss function has the form:

$$L = \frac{(e^{\alpha x_t} - ax_t - 1)}{\alpha^2} \tag{1}$$

where α is a constant and x_t is the forecast error at time *t*, defined as $x_t \equiv y_t - f_t$, where f_t is the forecast. The parameter α determines the degree of asymmetry. A Linex function with $\alpha = 0.7$ is plotted in Figure 1. A convenient property of the Linex loss function is that it nests the quadratic loss function as $\alpha \to 0$.[4]

Under the Linex loss function, optimistic forecasts (negative forecast errors) are more costly than pessimistic forecasts (positive forecast errors) when $\alpha < 0$. In this case, the loss is approximately exponential in x if $x < 0$, and approximately linear in x if $x > 0$. Conversely, if $\alpha > 0$, the Linex function is exponential to the right of the origin, and linear to the left. In this case, pessimistic forecasts (positive forecast errors) are more costly than optimistic forecasts (negative forecast errors).

[4] As $\alpha \to 0$, the numerator and the denominator of (1) tend to zero. Consequently, as $\alpha \to 0$, we employ L'Hospital's rule to obtain the quadratic form.

Assume initially earnings, $y_{t,}$ are generated by a conditional Gaussian process. Diebold and Christofferson (1996, 1997) show that under the Linex loss function (1), the optimal *h*-period ahead forecast, $f_{t,t+h}$, is given by:

$$f_{t,t+h} = E_t(\mu_{t+h}) + \frac{\alpha}{2} E_t(\sigma^2_{t+h})_t \qquad (2)$$

where $E_t(\mu_{t+h})$ is the expectation of the mean of y_{t+h} conditional on information at time *t* (and is the optimal forecast under quadratic loss) and $E_t(\sigma^2_{t+h})$ is the expectation of the conditional error variance over the *h* periods. Expression (2) tells us that the optimal forecast for a rational analyst with an asymmetric loss function, given by the Linex function (1), differs from the conditional mean, i.e. the forecast is biased. It is optimal for the analyst to produce optimistic forecasts if $\alpha > 0$. Diebold and Christofferson (1996, 1997) also show that the ex post forecast error, x_t , is given by:

$$x_t = -\frac{\alpha}{2} E_t(\sigma^2_{t+h}) + z_t \qquad (3)$$

where z_t is a zero mean moving average error process of order *h*- 1.

Expressions (2) and (3) indicate that the optimal bias for an asymmetric loss analyst depends positively on the loss function parameter, α , and on the variance of the forecast error. Thus, given that the forecast error variance, $E_t(\sigma^2_{t+h})$, is positive, if forecast errors are on average negative (forecasts are on average optimistic), this is consistent with a positive loss function parameter, α .

The optimal forecast expression (2) assumes that the outcome (earnings) series, $y_{t,}$, is a conditional Gaussian process. If we relax this assumption, it is possible to show that the optimal forecast and the forecast error depend on both the variance and the skewness of the forecast error process. The forecast error is given by:

$$v_t = G[E_t(\sigma^2_{t+h}), E_t(\sigma^3_{t+h})] + z^*{}_t \qquad (4)$$

where z^*_t is a moving average error process, $E_t(\sigma^3_{t+h})$ is the expectation of conditional skewness in the forecast error and G is a nonlinear, positive function of both the conditional variance and the conditional skewness of the forecast error process (see Appendix A for the proof).

Expressions (3) and (4) have important empirical implications, given that the distributions of earnings and earnings forecast errors are non-normal (e.g. Gu and Wu, 2003; Abarbanell and Lehavy, 2003). Under asymmetric loss, if $\alpha > 0$ then forecast bias is expected to depend on the positively on the variance of the forecast error. The theory also predicts that forecast errors will be positively related to skewness, although the association will be weak if the magnitude of α is small. In contrast, if the loss function is linear and symmetric (MAE), as assumed by Gu and Wu (2003), forecast bias depends *only* on the skewness of earnings (or forecast errors). This suggests that a simple test of whether analysts' loss functions are asymmetric is to examine dependence between forecast errors and the proxies for the conditional variance and conditional skewness of forecast errors. If only skewness is significant then this is consistent with analysts minimising absolute forecast errors. If variance of forecast error is a significant determinant of forecast errors then the hypothesis that analysts minimize absolute forecast error can be rejected in favour of an asymmetric loss function, under the maintained assumption of rational expectations.

3. Research design

We assume that analysts' loss functions take account of any scale-related component of forecast errors. Since analysts forecast earnings per share, the magnitude of raw forecast errors will depend on the "scale" of the stock. Holding the size of firms constant, a firm with *N* issued shares will have earnings per share forecast errors that are twice as large as an otherwise identical firm with *2N* issued shares. If we assume that costs associated with forecast errors are related to the proportionate valuation errors that could arise from use of forecasts, this suggests that the argument of the loss functions will be price-scaled forecast error.[5] However, while our main tests employ price-scaled forecast errors, in unreported sensitivity checks we also estimated regressions using un-scaled data. In this case, we scale *ERROR* and the prior periods' earnings change variables (*SUE*1 and *SUE*2) by stock price at *t*-1. Our tests are based on the empirical model in Gu and Wu (2003).[6] We extend their model by adding a proxy for the conditional variance and skewness of forecast errors. The main estimating equation is as follows:

$$\begin{aligned} ERROR_{it} &= b_0 + \lambda_1 ERRVAR_{it} + \lambda_2 ERRSKEW_{it} + b_1 \ln MVAL_{it} \\ &\quad + b_2 \ln ANFLL_{it} + b_3 LOSS_{it} + b_4 SUE1_{it} + b_5 SUE2_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

In line with Gu and Wu (2003), *ERROR* is defined as actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by beginning-of-period stock price. *ERRVAR* is defined as the second moment of the previous 8 quarters' scaled forecast errors for firm *i,* while *ERRSKEW* is the third moment of the previous 8 quarters' scaled forecast errors for firm *i*. *lnMVAL* is the natural logarithm of market value at the beginning of quarter *t* and is included to control for the possibility that analysts issue more biased forecasts for smaller companies in order to obtain access to management where less information is available (Francis and Willis, 2001). *lnANFLL* is the natural log of the number of analysts issuing forecasts for firm *i* in quarter *t* (Gu and Wu, 2003). We also include *LOSS* as an indicator variable (equal to 1 if the consensus forecast of earnings is negative, zero otherwise) because it has been argued that forecasts of losses are more optimistic (e.g. Duru and Reeb, 2002). *SUE*1 and *SUE*2 are included to control for analyst underreaction (e.g. Abarbanell and Bernard, 1992) and are defined as, respectively, the one period and two period lagged earnings surprise based on a seasonal random walk model.

[5] For example, suppose that intrinsic value is estimated using the P/E multiple approach and is a multiple of forecast earnings per share. Then the per share intrinsic value estimation error is proportional to the scaled forecast error.
[6] Although Gu and Wu's (2003) model forms the basis for our tests, there are differences between our model and theirs. For instance, they include measures of earnings variability and forecast variability as control variables in their test of the MAE loss function, whereas we include the variance of the forecast error as a central test of an asymmetric loss function. We note that theoretically it is the moments of forecast errors that are relevant determinants of any bias, and not the distribution of the variable to be forecast. Moreover, because we arrive at our predictions from a different theoretical standpoint to Gu and Wu, their estimates of skewness are based on a period before and after quarter *t*, whereas our tests are based only on ex ante estimates.

4. Empirical tests

4.1 Data

Our sample is drawn from the I/B/E/S detail history files for the period 1983 to 2003. To ensure consistency, we retrieve individual quarterly forecasts, actual earnings, earnings announcement dates and stock price data all from I/B/E/S. We require each firm to have at least eight consecutive quarters' actual earnings and forecast data in order to generate our measures of forecast error variance and skewness. We define the consensus forecast as the median of all forecasts issued within 90 days of the earnings announcement date. Forecast error (*ERROR*) is defined as actual earnings at time *t*, minus the consensus forecast, divided by stock price at the beginning of the forecast period, multiplied by 100. Negative errors therefore imply analyst optimism.

We measure error variance as the unstandardised variance of *ERROR* in the preceding eight periods, i.e., the sum of the squared deviations from the mean of *ERROR* over the previous eight quarters. Our measure of skewness is defined as the sum of the cubed deviations from the mean *ERROR* for the eight quarters prior to quarter *t*. In order to remove potential data errors, we winsorize the error and earnings related variables at the 1^{st} and 99^{th} percentiles, in line with previous research (Abarbanell and Lehavy, 2003). Our results are robust to alternative outlier deletion procedures (e.g. removing observations in the 5^{th} and 95^{th} percentiles).

4.2 Descriptive statistics

Our final sample comprises 79,653 firm quarters for 4,335 firms. Table 1, panel A, provides summary statistics. In line with prior research (e.g. Basu and Markov 2004), the sample-wide distribution of forecast error is negatively skewed, with the mean forecast error being negative (consistent with on-average optimism bias) and the median forecast error being slightly positive. Our measures of firm-specific ex ante error variance (*ERRVAR*) and skewness (*ERRSKEW*) both display a high degree of variability. The statistics for *LOSS* and *FLLW* show that approximately 10% of the firms in our sample were forecast to make a loss and the median number of analysts following each firm in quarter *t* is 6. Panel B provides reassurance that the forecast error distribution in our sample is consistent with the prior literature by comparing our sample with that in Abarbanell and Lehavy (2003). The comparison shows that the two samples are very similar, despite the forecast data being from different data sources.

Panel C of table 1 reports the correlations between variables. Particularly noteworthy is the high negative correlation between *ERRVAR* and *ERRSKEW*. This suggests the possibility that skewness could be serving a proxy role for variance in Gu and Wu (2003). Since dependence of the forecast error on variance is key empirical prediction that distinguishes the symmetric (linear) loss explanation of forecast bias from the asymmetric loss explanation, this characteristic of the data points to the importance of controlling for variance in evaluating these two competing explanations.

4.3 Regression results

Our main regression results are reported in Table 2. We estimate six versions of equation (5) including one or both of *ERRVAR* and *ERRSKEW* and both with and without control variables. In view of the clear non-normality in the distribution of forecast errors in table 1, the possibility exists that inferences are sensitive to heteroskedasticity and non-normality in regression errors. Therefore we report both OLS *t* –statistics (as in Gu and Wu, 2003) and *t* –statistics based on White robust standard errors.[7] Table 2 indicates that the White corrected *t*-statistics are often very much lower than the OLS *t*-statistics, and inferences regarding the significance of *ERRSKEW* are sensitive to the choice of test statistic. Breusch-Pagan (1979) tests rejected the null of constant variance in all reported models. We therefore rely on the more conservative White corrected *t*-statistics, where relevant.

[7] We also examined the sensitivity of inferences to use of exact critical values for the White standard errors obtained from the Wild bootstrap methodology. Although critical values obtained from the bootstrap methodology are much higher than classical values, indicating that non-normality is a significant problem, the main inferences are unchanged. Indeed, they are reinforced.

The results in table 2 generally confirm prior research. Models 3 and 6 reveal a significant *positive* association between *ERROR* and *ERRSKEW* when *ERRVAR* is excluded.[8] This is consistent with Gu and Wu (2003). Results for models 1 and 4 indicate that if *ERRSKEW* is replaced by *ERRVAR*, model specification improves (adjusted R^2 increases from 1.76% (5.48%) without (with) control variables to 2.73% (6.12%)). The sign of the coefficients on *ERRVAR* are negative, as predicted if positive forecast errors are more costly to analysts than negative forecast errors, i.e. if $\alpha > 0$. Results for models 2 and 5 indicate that the statistical significance of *ERRVAR* remains, even after controlling for *ERRSKEW*, and despite the high correlation between *ERRVAR* and *ERRSKEW* that would be expected to bias *t*-statistics towards zero.[9] Note, however, that when *ERRVAR* is included in the model, the sign of the coefficient on *ERRSKEW* in models 2 and 5 is *negative*, as predicted by the asymmetric loss function explanation of forecast bias, and in contrast to the positive coefficients in models 3 and 6. Further, based on White corrected *t*-statistics, the significance of *ERRSKEW* is at best marginal, whereas using OLS *t*-statistics *ERRSKEW* appears highly significant.

Generally the results in table 2 indicate that results are not sensitive to inclusion of control variables. Inferences regarding the significance of *ERRVAR* and *ERRSKEW* are identical for model 1-3 and for models 4-6. Therefore, in subsequent tests we focus on models 1-3. The estimated parameters for the control variables in models 4-6 are generally in line with the findings in prior research. Forecast errors are positively related to firm size (as captured by *lnMVAL*) in each of the reported models, suggesting that analysts are more optimistic when forecasting earnings of smaller firms. We further examine this issue below. There are significant negative coefficients on the analyst following variable (*lnANFLL*) and the loss variable (*FCLOSS*), both of which are consistent with Gu and Wu (2003). Like many previous studies (e.g., Abarbanell and Bernard, 1992; Easterwood and Nutt, 1999), there is also evidence of

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[8] Gu and Wu (2003) employ measures of variance and skewness based on the distribution of earnings. We use measures based on the distribution of forecast errors, to be consistent with theory. However, empirically, measures under the two approaches are highly correlated. If we replace our measures with measures similar to Gu and Wu (2003) we obtain qualitatively similar results to those reported here. Details are available from the authors.

[9] Despite the high univariate correlation between *ERRVAR* and *ERRSKEW*, all variance inflation factors in the multivariate analyses were well under the commonly used threshold of 10 (e.g., Chatterjee and Price, 1977).

underreaction to prior period earnings changes – coefficients on both *SUE*1 and *SUE*2 are significant and positive in each of models 4-6.

Overall, we interpret the results in table 2 as providing strong support for the conjecture that analyst forecast bias is associated with analysts having asymmetric loss functions, rather than linear symmetric loss functions. If analysts' loss functions are linear and symmetric, forecast errors should be a function of *ERRSKEW* but not *ERRVAR*, whereas asymmetric loss should result in the statistical significance of *ERRVAR,* with *ERRSKEW* having the same sign as *ERRVAR*. This is exactly what we find in our results.

4.4 Book-to-market and size portfolio analysis

The results reported in table 2 are based on a very large sample and unreported analysis reveals they are extremely robust to various model specification and variable measurement choices (see section 4.5 below). In this section we show that the findings reported above extend to portfolios sorted on a priori determinants of analyst forecast bias that are also correlates of forecast error variance and skewness. We consider the relation between forecast errors and *ERRVAR* and *ERSKEW* for portfolios sorted on the basis of book-to-market ratio and on market capitalization. If *ERRVAR* retains it ability to explain within-portfolio forecast errors, this constitutes an even more powerful test of the asymmetric loss function explanation.

We sort portfolios on the basis of these stock characteristics first because they are the basis of commonly used investment styles - book-to-market ratio is a common characteristic for distinguishing between value and glamour stocks. Doukas et al. (2002) show that analyst forecast bias differs significantly across portfolios sorted on these characteristics, although not in a direction capable of explaining the value premium the irrational extrapolation hypothesis. Second, recent research suggests that book-to-market is a useful instrument that captures the degree of accounting conservatism (Beaver and Ryan, 2005) and, that conservatism is an important determinant of the distributional properties of earnings and forecast errors (see, e.g., Basu, 1997; Helbok and Walker, 2004).

We form one-way sorted portfolios each quarter based on beginning-of-quarter book-to-price and on market capitalization. Table 3 confirms that forecast errors are indeed dramatically different across book-to-market ratio and market capitalization portfolios. The mean values of *ERROR* lie between -0.01% for low book-to-market stocks to -0.28% for high book-to-market stocks, indicating that the optimistic bias is much higher for high book-to-market stocks. Note also that the standard deviation of *ERROR* increases and the negative skewness decreases monotonically across book-to-market portfolios. In contrast the stock level estimates of *ERRVAR* and *ERRSKEW* indicate that forecast error variance increases dramatically with book-to-market and forecast error skewness is negative and decreases dramatically with book-to-market. Similar patterns are observed across size-sorted portfolios. The degree of optimistic bias in forecasts is much higher for small firms, and *ERRVAR* decreases dramatically as firms become larger, as does the extent to which *ERRSKEW* is negative. The patterns of *ERRVAR* and *ERRSKEW* across characteristic portfolios are consistent with the observed forecast error bias.

In Table 4 we estimate models 1-3 similar to table 2, but for the one-way sorted portfolios. Results are generally consistent with table 2.[10] Panel A reports results for portfolios sorted on book-to-market. The coefficient on *ERRVAR* when it is the sole independent variable is consistently negative, as predicted by the asymmetric loss function explanation, and significant at the 10% level or better. Similarly, the coefficient on *ERRVAR* in model 3 is positive and significant in three out of four cases. When both *ERRVAR* and *ERRSKEW* are included in the same regression (model 2), multi-collinearity problems become somewhat more severe but *ERRVAR* retains its significance for high book-to-market portfolios where forecast bias is greatest. The sign on *ERRSKEW* changes from positive to negative in three out of four cases, although it is significant in only one case.

[10] Additional (unreported) tests showed that the results in table 4 are not sensitive to the inclusion of the control variables.

Results in table 4 panel B for size-sorted portfolios are similar. *ERRVAR* is negative and significant for all portfolios in model 1, while *ERRSKEW* is positive and significant. When *ERRVAR* and *ERRSKEW* are entered jointly, only *ERRVAR* is significant (in three cases at better than the 10% level) . *ERRSKEW* is insignificant in all cases. Again, multi-collinearity does present a problem for some portfolios, especially in the case of the larger firm portfolios, and this explains why *ERRVAR* loses significance when *ERRSKEW* is added.

Overall, the results in table 4 confirm that the variance of forecast errors is a significant determinant of forecast bias, even after first sorting firms into portfolios based on stock characteristics that sharply discriminate between different levels of forecast bias and forecast error variance and skewness. The continued significance of *ERRVAR* as an explanatory factor for forecast errors supports the earlier evidence in favour of the conjecture that financial analysts form their forecasts with reference to asymmetric loss functions.

4.5 Robustness checks

The results we have reported are based on price-scaled forecast errors. We believe that there are good reasons for scaling, based on considering the links between forecast errors and the costs borne by users of earnings forecasts (see e.g. footnote 5). However, there is accumulating evidence that scaling may have perverse effects on the distributional properties of variables (see, e.g., Cohen and Lys, 2003; Durtschi and Easton, 2004; Lambert, 2004). For this reason, we also employed the Wild bootstrap methodology to both price-scaled and un-scaled data and identified critical values for relevant test statistics (e.g. Davidson and Flachaire, 2001). This methodology utilizes the distribution of the error term in the main estimating equation to simulate empirical confidence intervals necessary to reject the null hypothesis when the null holds. It provides a powerful test of statistical significance when the underlying regression error distribution is non-normal (Wu, 1986; Hardle and Mammen, 1993). Use of the Wild bootstrap can result in critical values differing dramatically from classical values. For example, according to our estimates, critical values to allow rejection of the hypothesis that skewness is significantly different from zero are up to 74% higher than the classical value (for $p < 0.05$) for un-scaled data. Despite this, in unreported results we find that all the inferences drawn from the main results reported in table 2 remain intact, after taking account of the bootstrapped critical values.

As a further robustness check, we also estimated Models 1–6 using least absolute deviation (LAD) regression, as used by Basu and Markov (2004) and Fama MacBeth (1973) regressions. The results (not reported) are again consistent with those reported in Tables 2 and 4.

5. Conclusions

Previous research has consistently found evidence of bias and inefficiency in financial analysts' forecasts of earnings. Recent research by Gu and Wu (2003) and Basu and Markov (2004) has examined the possibility that these findings are attributable to an unrealistic assumption of a quadratic loss function, and has concluded that analysts' objective is to minimise the mean absolute forecast error (MAE), rather than mean squared error. The mean absolute error loss function penalises forecast optimism and pessimism equally. The explanation for forecast bias is attributable to skewness in the distribution of earnings. However, numerous studies suggest that analysts' motives may be driven by the costs associated with under-predicting earnings being higher than the costs of over-predicting earnings, i.e. asymmetric loss functions. Asymmetric loss functions could result from incentives to gain access to management and/or more favourable career prospects for analysts who are systematically optimistic (e.g., Lim, 2001; Hong and Kubik, 2003). In this paper, we test whether analysts' forecasts are consistent with loss functions being asymmetric.

Under the MAE loss function, forecast error is a function only of forecast error skewness. In contrast, under the asymmetric Linex loss function, ex post error is also a function of error variance. Our results indicate that the linear symmetric loss function of MAE can be rejected in favour of the Linex function. We find that forecast error is more strongly related to prior forecast error variance than to skewness. Indeed, when forecast error variance is included in forecast error regressions, the sign on forecast error skewness changes. These results strongly suggest that analysts have asymmetric loss functions.

Our results have important implications for the interpretation of analysts' forecasts. The assumption that analysts' objective is solely to minimise forecast error may be inappropriate. As pointed out by Lambert (2004), it is investors', rather than analysts', loss functions that are ultimately most important in determining security prices. However, to the extent that analysts' forecasts influence investors' decision making, an understanding of the shape of analysts' loss function is necessary to enable investors to consider adjustment for potential biases.

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Appendix A

Expanding the Linex function (1) to a fourth-order Taylor approximation we obtain

$$L = \frac{(e^{\alpha x_t} - ax_t - 1)}{\alpha^2} \cong \frac{x^2}{2} + \frac{\alpha x^3}{6} + \frac{\alpha^2 x^4}{24} \qquad \text{(A1)}$$

Noting that $x \equiv y - f$ and minimising L with respect to the forecast, we obtain

$$\frac{dL}{df} = x + \frac{\alpha x^2}{2} + \frac{\alpha^2 x^3}{6} = 0 \qquad \text{(A2)}$$

Taking expectations of (A2) we obtain the cubic equation:

$$E[x + \frac{\alpha x^2}{2} + \frac{\alpha^2 x^3}{6}] = 0 \qquad \text{(A3)}$$

Let $Z = E(y) - f$ and $y - E(y) = \varepsilon$. Noting that

$$x^2 = (y - Ey + Ey - f)^2 = (y - Ey + Z)^2 \text{ and}$$
$$x^3 = (y - Ey + Ey - f)^3 = (y - Ey + Z)^3$$

we obtain

$$Z + \frac{\alpha}{2}(\sigma_\varepsilon^2 + Z^2) + \frac{\alpha^2}{6}(\sigma_\varepsilon^3 + 3\sigma_\varepsilon^2 Z + Z^3) = 0 \qquad \text{(A4)}$$

where $\sigma_\varepsilon^3 = E(\varepsilon^3) = E(y - E(y))^3$.

Rearranging (A4) we obtain equation (4) in text.

Note that if we approximate (A1) to order 3 we obtain

$$Z + \frac{\alpha}{2}(\sigma_\varepsilon^2 + Z^2) = 0 \text{ .}$$

Therefore

$$Z + \frac{\alpha}{2}Z^2 = -\frac{\alpha}{2}\sigma_\varepsilon^2 \text{ .}$$

If $\alpha > 0$ then Z becomes more negative - and hence optimism bias increases - as the forecast error variance increases. In other words, the degree of optimism is a positive function of the forecast error variance. This is consistent with the closed form result of Diebold and Christofferson (1996, 1997) in expression (3).

Expression (A4) can be rewritten as follows:

$$Z + \frac{\alpha^2}{2}\sigma_\varepsilon^2 Z + \frac{\alpha}{2}Z^2 + \frac{\alpha^2}{6}Z^3 + \frac{\alpha}{2}\sigma_\varepsilon^2 + \frac{\alpha^2}{6}\sigma_\varepsilon^3 = 0 \qquad \text{(A5)}$$

If the sum of the last two terms in (A5) is positive, then the equation has two complex roots and one real root. By inspection, ceteris paribus, irrespective of the sign of α, Z is a negative function of σ_ε^3 (and optimism bias is a positive function of σ_ε^3). In other words, the signs on the coefficients on both forecast error variance and forecast error skewness should be negative for $\alpha > 0$. Note that if forecast error skewness is negative, skewness will partially offset the optimism bias induced by forecast error variance. However, generally, the marginal impact of skewness will be dominated by the variance effect when $|\alpha| < 1$.

Note that while the above analysis has been conducted in the context of the Linex loss function, it is applicable, any continuous loss function to order four will generate a quartic expression analogous to expression (A1) and hence forecast error variance and skewness will be determinants of bias, in contrast to symmetric loss functions where variance plays no role.

Fig. 1: Linex loss function for $\alpha = 0.7$

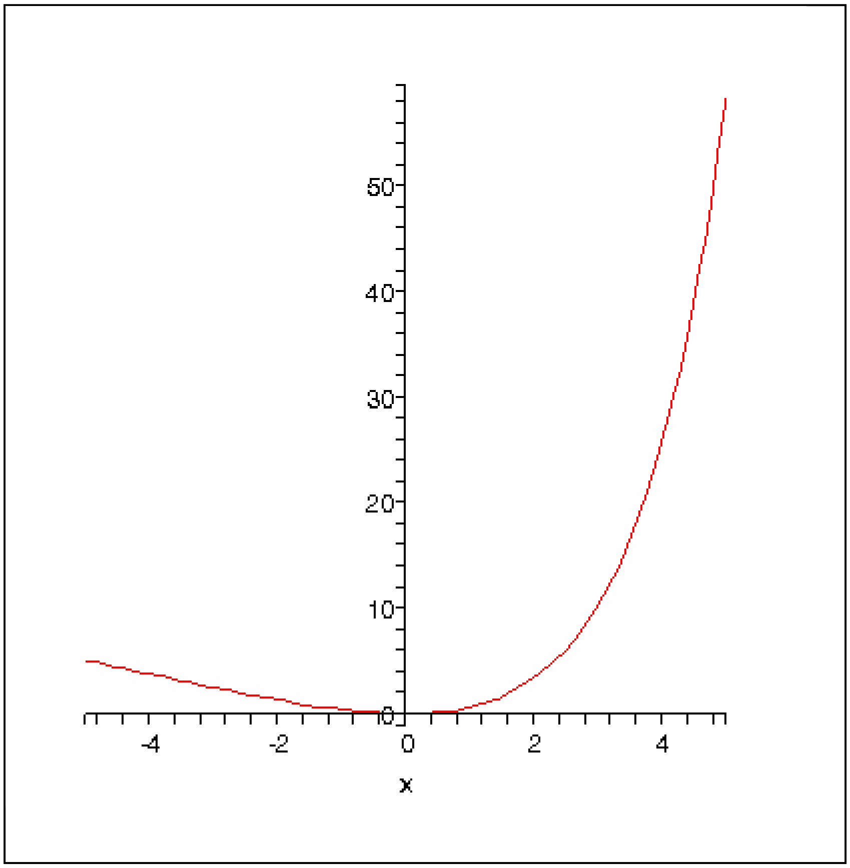

Table 1
Panel A: Descriptive Statistics (n=79,653)

Variable	Mean	Median	Std. dev.	Skewness
ERROR	-0.1074	0.0125	1.10	-4.77
ERRVAR	10.0099	0.4005	44.0940	6.52
ERRSKEW	-46.4005	-0.0001	321.6870	-7.88
MVAL (mil $)	4,815	1046	17268	12.17
ANFLL	8.7291	6.0000	8.13	2.39
LOSS	0.1054	0.0000	0.31	2.57
SUE1	-0.0412	0.1521	1.93	-1.06
SUE2	-0.0319	0.1542	1.85	-1.13

Panel B: Comparison of Forecast Error (*ERROR*) Distribution with Abarbanell and Lehavy (2003) Sample

	Our sample (N = 79,653)	Abarbanell and Lehavy (2003) (N = 33,548)
Mean	-0.107	-0.126
Median	0.012	0.000
% positive	51%	48%
% negative	37%	40%
% zero	12%	12%
5^{th} percentile	-1.209	-1.333
10^{th} percentile	-0.561	-0.653
25^{th} percentile	-0.103	-0.149
75^{th} percentile	0.131	0.137
90^{th} percentile	0.404	0.393
95^{th} percentile	0.727	0.684

Panel C: Correlation Coefficients

	ERROR	*ERRVAR*	*ERRSKEW*	*lnMVAL*	*LNANFLL*	*LOSS*	*SUE1*
ERRVAR	-0.1654‡						
ERRSKEW	0.1327‡	-0.8702‡					
lnMVAL	0.1159‡	-0.1703‡	0.1102‡				
lnANFLL	0.0389‡	-0.0878‡	0.0597‡	0.5660‡			
LOSS	-0.1335‡	0.1428‡	-0.0806‡	-0.2153‡	-0.0711‡		
SUE1	0.1540‡	-0.0236‡	0.0380‡	0.0848‡	0.0255‡	-0.2423‡	
SUE2	0.1137‡	-0.0516‡	0.0454‡	0.0944‡	0.0318‡	-0.2144‡	0.4681‡

Notes:
‡ indicates significance at the 0.001 level.
Variable definitions for each firm quarter:
ERROR is actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by stock price at the beginning of the quarter, expressed as a percentage.
ERRVAR is the second moment of the price-deflated previous 8 quarters' forecast errors expressed as a percentage.
ERRSKEW is the third moment of the price-deflated previous 8 quarters' forecast errors expressed as a percentage.
MVAL is the market value of common equity at the beginning of the quarter (in $millions).
ANFLL is the number of analysts issuing forecasts for each firm in the quarter the forecast falls in.
LOSS is an indicator variable equal to 1 if the consensus forecast of earnings is negative, zero otherwise.
SUE1 and *SUE2* are the price-deflated seasonal unexpected earnings from a random walk at quarters *t*-1 and *t*-2 respectively (expressed as a percentage).
In relation to panel C, we compare our sample with that of Abarbanell and Lehavy (2003). Abarbanell and Lehavy (2003) use the Zacks database from 1985 – 1998; we use I/B/E/S from 1983 – 2003. Both samples are winsorized at the 1st and 99th percentiles. Forecast error is defined (in both cases) as price-deflated quarterly actual earnings minus the forecast multiplied by 100.

Table 2
Price-Deflated Forecast Error Regressions

Model 1:

$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + \varepsilon_{it}$$

Model 2:

$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + \lambda_2 ERRSKEW \ + \varepsilon_{it}$$

Model 3:

$$ERROR_{it} = b_0 + \lambda_2 ERRSKEW_{it} + \varepsilon_{it}$$

Model 4:

$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + b_1 \ln MVAL_{it} + b_2 \ln ANFLL_{it} + b_3 LOSS_{it} + b_4 SUE1_{it} + b_5 SUE2_{it} + \varepsilon_{it}$$

Model 5:

$$ERROR_{it} = b_0 + \lambda_1 ERRVAR_{it} + \lambda_2 ERRSKEW_{it} + b_1 \ln MVAL_{it} + b_2 \ln ANFLL_{it} + b_3 LOSS_{it} + b_4 SUE1_{it} + b_5 SUE2_{it} + \varepsilon_{it}$$

Model 6:

$$ERROR_{it} = b_0 + \lambda_2 ERRSKEW_{it} + b_1 \ln MVAL_{it} + b_2 \ln ANFLL_{it} + b_3 LOSS_{it} + b_4 SUE1_{it} + b_5 SUE2_{it} + \varepsilon_{it}$$

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*
Constant	-0.0660‡	-0.0633‡	-0.0863‡	-0.3692‡	-0.3626‡	-0.4291‡
	(-19.24)	(-17.44)	(-24.18)	(-18.37)	(-17.71)	(20.58)
	[-16.71]	[-15.94]	[-22.06]	[-20.70]	[-20.27]	[-24.19]
ERRVAR	-0.0041‡	-0.0051‡	-	-0.0035‡	-0.0042‡	-
	(-13.91)	(-7.98)	-	(-12.14)	(-6.55)	-
	[-47.32]	[-28.98]	-	[-40.07]	[-23.80]	-
ERRSKEW	-	-0.0002	0.0005‡	-	-0.0001	0.0004‡
	-	(-1.86)	(11.62)	-	(-1.32)	(10.22)
	-	[-6.51]	[37.79]	-	[-4.66]	[32.47]
lnMVAL	-	-	-	0.0551‡	0.0543‡	0.0619‡
	-	-	-	(18.56)	(18.15)	(20.15)
	-	-	-	[18.96]	[18.66]	[21.33]
lnANFLL	-	-	-	-0.0343‡	-0.0341‡	-0.0352‡
	-	-	-	(-6.46)	(-6.42)	(-6.60)
	-	-	-	[-6.72]	[-6.69]	[-6.87]
LOSS	-	-	-	-0.2272‡	-0.2219‡	-0.2622‡
	-	-	-	(-9.57)	(-9.32)	(-10.82)
	-	-	-	[-17.28]	[-16.82]	[-19.97]
SUE1	-	-	-	0.0649‡	0.0655‡	0.0622‡
	-	-	-	(10.37)	(10.47)	(9.92)
	-	-	-	[28.86]	[29.09]	[27.56]
SUE2	-	-	-	0.0196‡	0.0196‡	0.0204‡
	-	-	-	(3.25)	(3.24)	(3.36)
	-	-	-	[8.40]	[8.38]	[8.72]
Adjusted R^2	0.0273	0.0278	0.0176	0.0612	0.0615	0.0548
F- value	193.48	96.73	135.04	133.23	114.46	132.31
N	79,653	79,653	79,653	79,653	79,653	79,653

Notes:
‡ indicates coefficients are significantly different from zero at the 0.01 level in two-tailed tests based on White's corrected standard errors.
t-statistics based on White's standard errors are in parentheses; OLS *t*-statistics are in square brackets.
ERROR is actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by stock price at the beginning of the quarter, expressed as a percentage.
ERRVAR is the second moment of the price-deflated previous 8 quarters' forecast errors expressed as a percentage.
ERRSKEW is the third moment of the price-deflated previous 8 quarters' forecast errors expressed as a percentage.
lnMVAL is the natural log of market value of common equity at the beginning of the quarter (in $millions).
lnANFLL is the natural log of the number of analysts issuing forecasts for each firm in the quarter the forecast falls in.
LOSS is an indicator variable equal to 1 if the consensus forecast of earnings is negative, zero otherwise.
SUE1 and *SUE2* are the price-deflated seasonal unexpected earnings from a random walk at quarters *t*-1 and *t*-2 respectively, expressed as a percentage.

Table 3

Summary statistics for book to market (BM) portfolios and size (S) portfolios

Panel A: Book-to-market portfolios	*N*	Mean	Median	Std. dev.	Skewness	Kurtosis
ERROR						
BM1 (Low)	15,925	-0.0114	0.0169	0.5881	-7.58	120.92
BM2	15,926	-0.0241	0.0116	0.6470	-5.76	83.90
BM3	15,925	-0.0733	0.0086	0.8394	-5.16	53.24
BM4 (High)	15,925	-0.2807	0.0000	1.6633	-3.14	17.26
ERRVAR						
BM1 (Low)	15,925	3.6730	0.0675	27.3944	11.30	137.65
BM2	15,926	4.3658	0.1977	28.2281	10.66	125.40
BM3	15,925	6.3278	0.4989	32.2876	8.78	87.03
BM4 (High)	15,925	20.3813	1.9693	60.1455	4.39	22.62
ERRSKEW						
BM1 (Low)	15,925	-16.0945	0.0000	198.1559	-13.48	188.80
BM2	15,926	-18.4755	0.0000	205.7084	-12.72	169.56
BM3	15,925	-27.0970	-0.0011	239.3229	-10.46	116.73
BM4 (High)	15,925	-95.4220	-0.0342	445.6831	-5.38	31.68

Table 3 (continued)

Summary statistics for book to market (BM) portfolios and size (S) portfolios

Panel B: Size portfolios	*N*	Mean	Median	Std. dev.	Skewness	Kurtosis
ERROR						
S1 (Small)	19,913	-0.3226	0.000	1.7887	-2.96	15.61
S2	19,914	-0.0700	0.0174	0.9244	-4.82	46.85
S3	19,913	-0.0293	0.0178	0.6999	-5.86	74.00
S4 (Large)	19,913	-0.0077	0.0161	0.5044	-8.06	141.32
ERRVAR						
S1 (Small)	19,913	21.8062	1.6531	64.9455	4.20	20.49
S2	19,914	8.7271	0.4726	41.2767	7.11	55.67
S3	19,913	6.3959	0.2807	33.3614	8.32	77.96
S4 (Large)	19,913	3.1105	0.0989	23.2653	12.45	172.16
ERRSKEW						
S1 (Small)	19,913	-103.9603	-0.0312	474.9499	-5.11	28.52
S2	19,914	-37.0994	-0.0001	290.8626	-8.84	82.25
S3	19,913	-28.6002	0.0000	252.3109	-10.10	107.77
S4 (Large)	19,913	-15.9423	0.0000	188.3161	-13.75	198.42

Notes:
ERROR is actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by stock price at the beginning of the quarter, expressed as a percentage.
ERRVAR is the second moment of the price-deflated previous 8 quarters' forecast errors expressed as a percentage.
ERRSKEW is the third moment of the price-deflated previous 8 quarters' forecast errors expressed as a percentage.
BM represents book-to-market portfolios (where 1 is the lowest B/M quartile and 4 is the highest B/M quartile).
S represents size portfolios (where S1 comprises the quartile of smallest companies in the full sample and S4 comprises the largest).

Table 4

Regressions of models 1-3 by book to market (BM) portfolios and size (S) portfolios

Panel A: Book-to-market portfolios	*Model 1*				*Model 2*				*Model 3*			
	BM1 (low)	BM2	BM3	BM4 (high)	BM1 (low)	BM2	BM3	BM4 (high)	BM1 (low)	BM2	BM3	BM4 (high)
Constant	-0.0016	-0.0180‡	-0.0600‡	-0.2026‡	-0.0001	-0.0221‡	-0.0531‡	-0.2003‡	-0.0069	-0.0194‡	-0.0695‡	-0.2400‡
	(-0.39)	(-3.75)	(-9.68)	(-16.36)	(-0.02)	(-3.90)	(-7.31)	(-15.86)	(-1.66)	(-3.98)	(-10.94)	(-19.20)
ERRVAR	-0.0027†	-0.0014	-0.0021‡	-0.0038‡	-0.0040	0.0013	-0.0053‡	-0.0043‡	-	-	-	-
	(-2.56)	(-1.88)	(-3.21)	(-8.28)	(-1.70)	(0.58)	(-2.65)	(-4.79)	-	-	-	-
ERRSKEW	-	-	-	-	-0.0002	0.0004	-0.0005	-0.0001	0.0003†	0.0003‡	0.0001	0.0004‡
	-	-	-	-	(-0.66)	(1.39)	(-1.95)	(-0.57)	(2.04)	(2.66)	(1.92)	(6.95)
R^2	0.0155†	0.0037	0.0065‡	0.0192‡	0.0165†	0.0072†	0.0109‡	0.0193‡	0.0089†	0.0065‡	0.0015	0.0131‡
F-value	6.57	3.53	10.34	68.48	3.36	3.63	5.45	34.19	4.14	7.07	3.69	48.34
N	15,925	15,926	15,925	15,925	15,925	15,926	15,925	15,925	15,925	15,926	15,925	15,925

Table 4 (continued)

Regressions of models 1-3 by book to market (BM) portfolios and size (S) portfolios

Panel B: Size portfolios	*Model 1*				*Model 2*				*Model 3*			
	S1 (small)	S2	S3	S4 (large)	S1 (small)	S2	S3	S4 (large)	S1 (small)	S2	S3	S4 (large)
Constant	-0.2044‡	-0.0515‡	-0.0214‡	-0.0034	-0.2018‡	-0.0481‡	-0.0210‡	-0.0024	-0.2572‡	-0.0632‡	-0.0255‡	-0.0054
	(-18.02)	(-8.71)	(-4.71)	(-1.00)	(-16.83)	(-7.69)	(-4.43)	(-0.71)	(-22.12)	(-10.22)	(-5.35)	(-1.60)
ERRVAR	-0.0054‡	-0.0021‡	-0.0012‡	-0.0014†	-0.0059‡	-0.0035‡	-0.0014	-0.0024	-	-	-	-
	(-11.88)	(-4.08)	(-2.73)	(-2.13)	(-5.90)	(-3.20)	(-1.37)	(-1.73)	-	-	-	-
ERRSKEW	-	-	-	-	-0.0001	-0.0002	-0.0000	-0.0001	0.0006‡	0.0002‡	0.0001†	0.0001
	-	-	-	-	(-0.56)	(-1.59)	(-0.25)	(-0.76)	(10.31)	(2.69)	(2.34)	(1.75)
R^2	0.0388‡	0.0090‡	0.0034‡	-0.0042†	0.0388‡	0.0105‡	0.0034†	0.0045	0.0280‡	0.0034‡	0.0023†	0.0029
F-value	141.03	16.67	7.46	4.56	70.58	8.73	3.75	2.86	106.30	7.26	5.49	3.05
N	19,913	19,914	19,913	19,913	19,913	19,914	19,913	19,913	19,913	19,914	19,913	19,913

Notes:
Models are as reported in Table 2.
S represents size portfolio, where S1 comprises the quartile of smallest companies in the full sample (*N* = 79,653), while S4 comprises the largest.
BM represents book to market portfolio, where BM1 comprises the lowest quartile of companies with data available (*N* = 63,701), while BM4 comprises the highest.
‡, † indicate significance at the 0.01 and 0.05 level respectively; *t*-statistics based on White's standard errors are in parentheses.
Dependent variable (*ERROR*) is actual quarterly earnings taken from I/B/E/S minus the median of all forecasts of quarterly earnings issued within 90 days of the earnings announcement, scaled by stock price at the beginning of the quarter, expressed as a percentage.
ERRVAR is the second moment of the price-deflated previous 8 quarters' forecast errors, expressed as a percentage.
ERRSKEW is the third moment of the price-deflated previous 8 quarters' forecast errors, expressed as a percentage.