Measuring the Information Environment of Biased Forecasts: A Reexamination of the Information Content around Earnings Announcements

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Abstract

Previous studies suggest that analysts are overconfident when making forecasts (Chen and Jiang 2006; Zhang 2006; DeBondt and Thaler 1990). We extend this intuition and broaden the measure of information content devised by Barron et al. (1998) to a more general setting in which analysts irrationally weigh public and private information in making forecasts. We propose a model to estimate the actual (biased) weights and the theoretical (unbiased) weights of the private and public information contained in analyst forecasts. We then apply the model to reexamine the information content of analyst forecasts around earnings announcements, and find that analysts overweight private information after earnings announcements, and that the proportion of private information in analyst forecasts decreases significantly after these announcements.

Keywords: Analysts’ forecasts; Public information; Private information; Consensus; Earnings announcements;

Data availability: All data are available from public sources.
I. Introduction

Analyst forecasts dispersions have been widely used to capture both information asymmetry (Barron et al. 2002; Frankel et al. 2006) and uncertainty (Johnson 2004). However, recent papers (Chen and Jiang 2006; Zhang 2006) have found significant biases in analyst forecasts. When overconfident analysts make forecasts, the observed forecast dispersion reflects information asymmetry, uncertainty, and a certain level of hubris. If we fail to account for these biases in forecasts, then our estimates of information asymmetry and uncertainty are likely to be flawed.

Barron, Kim, Lim, and Stevens (1998, hereafter BKLS) provide a theoretical model that decomposes analyst forecasts into common (public) and idiosyncratic (private) information. Their measure has greatly enriched the literature by allowing researchers to examine the information environment for many different situations. For instance, Barron et al. (forthcoming) examine the relation between analyst forecast dispersion and stock returns. Mohanram and Sunder (2006) find that analysts have been investing more effort in the discovery of idiosyncratic information since the Regulation Fair Disclosure. Botosan et al. (2004) find a positive relationship between private information and the cost of equity capital, and Barron et al. (2002) find that the idiosyncratic information contained in individual analyst forecasts increases immediately after earnings announcements. However, the BKLS measure assumes that analysts rationally weigh public and private information when producing forecasts, an assumption that is challenged by the finding in Chen and Jiang (2006) that analysts display strong biases by overweighting private information when they forecast corporate earnings. DeBondt and Thaler (1990) and Zhang (2006) also suggest that analysts are optimistically biased when making forecasts. As the conditional expectation of earnings is a weighted average of the common (public) and idiosyncratic (private) information available when forming the expectation, the outcomes are likely to
differ if the weights used in the BKLS model fail to capture the bias of the optimistic weighting of private information by analysts.

In this paper, we examine the BKLS measure and show that it leads to inaccurate classifications of information content by overstating idiosyncratic information when analysts place more weight than is efficient on private information. We extend the BKLS model and propose a more generalized approach by allowing the weights of private and public information to deviate from the rational weights. We show that the BKLS model holds only when the actual “irrational” weights are equal to the theoretical “rational” weights. Using our revised model, we find, consistent with Chen and Jiang (2006), that the weights of private information used to formulate earnings forecasts are significantly higher than the rational weights around earnings announcements. Interestingly, we also find that the proportion of idiosyncratic information in a forecast experiences a significant decline and the proportion of public information significantly increases after earnings announcements. Our findings support the proposition that earnings announcements reduce information uncertainty and discourage analysts from obtaining private information. Our conclusions differ from those of Barron et al. (2002), who find a significant large increase in private information and a decrease in public information after earnings announcements. Our model compliments the BKLS model, and interpretations of our empirical results are consistent with the findings in Ivkovic and Jegadeesh (2004) and Hui and Yeung (2007).

Our study contributes to the literature in several ways. We show how analyst biases affect the forecast dispersion, and point out that forecast dispersion reflects more than just uncertainty and information asymmetry, as stated in the literature. We extend the widely-used BKLS measure and explicitly model the biases in analyst weighting of idiosyncratic and common information. We analyze the information environment after earnings announcements, and show how the dynamics of information operate in different ways from those documented in the literature. We also demonstrate
how our measure complements recent empirical findings that report a lower private information content relative to public information after earnings announcements.

The remainder of the paper is organized as follows. Section II reviews the literature on the information environment around earnings announcements. Section III presents our model. Section IV discusses the sample selection, research design, and empirical results. Section V presents some robustness tests. Finally, Section VI concludes.

II. The Information Environment around Earnings Announcements

Extant theories offer two competing explanations of why analyst forecast dispersion narrows after corporate disclosure. Some authors (Diamond 1985; Kim and Verrecchia 1991; Healy and Palepu 2001) argue that dispersion narrows because corporate disclosures lower the information uncertainty and reduce the incentives for analysts to seek new information (i.e., public information increases and private information does not change after information disclosure). Others (Kim and Verrecchia 1994, 1997; Kandel and Pearson 1995) find that corporate disclosure triggers analysts to acquire more private information, and that the smaller forecast dispersion reflects a higher quality of analyst forecasts (i.e., private information increases after information disclosure).

Several theoretical models (Holthausen and Verrecchia 1988; Demski and Feltham 1994; Subramanyam 1996) suggest that analyst forecasts or reports are less important for Bayesian investors if public information is timely. The implication is that there is no significant change in the private information produced by analysts because public information greatly alleviates future information uncertainty. In contrast, Lang and Lundholm (1996) suggest that analyst reports provide information that is complementary to earnings announcements. Francis et al. (2002) similarly find that information disclosed in earnings announcements does not reduce the usefulness of other information sources, such
as analyst forecasts. Frankel et al. (2006) also show that the information contained in earnings announcements and the information given in analyst reports are complementary.

Barry and Jennings (1992) and Abarbanell et al. (1995) suggest that forecast dispersion represents both future uncertainty and information asymmetry. Barron et al. (forthcoming) use the BKLS model and attempt to separate forecast dispersion into uncertainty and information asymmetry, demonstrating that changes in dispersion primarily reflect changes in information asymmetry whereas the level of dispersion primarily reflects the level of uncertainty. They conclude that earnings announcements lead to increased information asymmetry even though they may also lower the uncertainty about some firms. Barron et al. (2005) also find strong evidence that investors trade because the level of private information increases after earnings announcements. Indirect support for these ideas can also be found in Krinsky and Lee (1996) and Kandel and Pearson (1995), who find that the asymmetry information component of the bid-ask spread increases and the trading volume rises around earnings announcements. Lee et al. (1993) suggest that liquidity providers are sensitive to changes in information asymmetry risk and use spreads and depth to manage such risk. Finally, Barron et al. (2002) show that the proportion of private information increases significantly after earnings announcements, and conclude that accounting disclosures induce the production of private information.

However, empirical evidence regarding the information environment around earnings announcements continues to be mixed. Ivkovic and Jegadeesh (2004) find that the information content of analyst forecasts is weakest after earnings announcements because it has the least impact on the market price, which is clearly inconsistent with the interpretation of a higher level of private information after earnings announcements. Hui and Yeung (2007) also express serious concern about the interpretations in Barron et al. (2002), and suggest that the decrease in forecast consensus is driven by analysts’ use of public information. Their results support the proposition that earnings announcements
produce greater public information and reduce information uncertainty without causing an increase in idiosyncratic information.

To better discern the information content in analyst forecasts, it is necessary to consider the inherited biases within them. Chen and Jiang (2006) point out that analysts place a larger than efficient weight on private information when making forecasts. The literature (DeBondt and Thaler 1990; Abarbanell and Bernard 1992; Zhang 2006) shows that analyst forecasts are biased due either to cognitive bias or to economic incentives. Therefore, we need to examine whether the model of analyst expectations and the measure of idiosyncratic information accurately characterize the biases in earnings forecasts.

III. The Model

This section generalizes the BKLS model to a situation in which analysts fail to place the “rational” weights on public and private information when making forecasts.

The BKLS model assumes that forecasts reflect the information that analysts possess in an unbiased way,¹ and shows that one can compute the precision of public and private information using the following formula.

\[
\begin{align*}
\text{Public information: } h &= \frac{(SE - \frac{D}{N})}{[SE - \frac{D}{N} + D]^2} \\
\text{private information: } s &= \frac{D}{[SE - \frac{D}{N} + D]^2},
\end{align*}
\]

where \(SE\) is the expected squared error in the mean forecast, \(D\) is the expected forecast dispersion, and \(N\) is the number of forecasts.

¹ Barron et al. (1998) also discuss the implications of optimistic forecasts on their model, and advise researchers to be aware of its limitations and caveats. However, they do not offer a solution to address this concern.
We follow the framework in Barron et al. (1998) and consider a firm for which $N$ financial analysts forecast earnings. In the notation, $y$ denotes the actual earnings, which we assume to follow a normal distribution. An analyst’s information set at the time of forecasting is a combination of two sets: a set of public information that is observed by all analysts and a set of private information that is observed only by that particular analyst. Let $z_t$ be the public information at time $t$

$$z_t = y + \varepsilon_t,$$  

(1)

where the noise term is $\varepsilon_t \sim N(0, \frac{1}{h_t})$ and is independent of $y$. $h_t$ is the precision of the public information. Intuitively, if the level of precision is high, then the noise term $\varepsilon_t$ will approach zero. Let $q_{it}$ be the private information of analyst $i$ about $y$ at time $t$

$$q_{it} = y + \mu_{it},$$

(2)

where $\mu_{it} \sim N(0, \frac{1}{s_{it}})$ and is independent of $y$ and $\varepsilon_t$. Similarly, $s_{it}$ is the level of precision of the private information of analyst $i$, where $\mu_{it}$ is also mutually independent.

We further assume that both public information and private information arrive randomly, and that once analysts receive public or private information, they make a forecast. An analyst’s best (rational) conditional estimate of $y$ given $z_t$ and $q_{it}$ is formed by the Bayes’ rule

$$f_{it} = E(y \mid z_t, q_{it}) = \beta_{it} q_{it} + (1 - \beta_{it}) z_t,$$

(3)

where

$$\beta_{it} = \frac{s_{it}}{s_{it} + h_{it}}.$$  

(4)
is the efficient weight placed on the private information, which minimizes the mean-squared error of the forecast. Hence, $1 - \beta_i$ is the efficient weight for the public information. Intuitively, if the private information is more accurate, then an analyst will place greater weight on it.

In reality, analysts may deviate from the efficient weight either incautiously (overconfidence bias) or intentionally (optimistically weighting the information to generate trading business). If such bias exists, then we assume the actual weight of the private information to be $k_{it}$. The expectation can then be expressed as follows.

$$f_{it} = k_{it} q_{it} + (1 - k_{it}) z_t.$$  \hspace{1cm} (5)

$k_{it}$ may equal the efficient weight $\beta_i$ (a rational case), may be greater than the efficient weight (an over-confidence case), or may be less than the efficient weight (a herding case).

Similar to Barron et al. (1998) and Chen and Jiang (2006), we adopt an ex-post perspective by using earnings forecasts and realized actual earnings to investigate the information environment around earnings announcements. Assuming that all analysts produce forecasts at the same time immediately before the information disclosure at time $T$, we define the average forecast as follows.

$$f = \frac{1}{N} \sum_i f_{it}.$$  

The forecast dispersion then becomes

$$d = \frac{1}{N - 1} \sum_{i=1}^N (f_{it} - f)^2,$$

with unconditional expectation
\[
D = E(d) = \frac{1}{N-1} \sum_{i=1}^{N} (\text{Var}(f_{iT} - f)), \tag{6}
\]

forecast error

\[e = y - f,\]

and expectation

\[SE = E(e^2) = E(y - f)^2. \tag{7}\]

In the following propositions, we establish the relations among \(D, SE\), and several information variables. The proof is presented in the appendix.

**Proposition 1**

At time \(T\), if all of the private information has the same level of precision, that is, \(s_{iT} = s\), and all analysts use the same weight, \(k_{iT} = k\), then

\[s = k^2 / D, \tag{8}\]

\[h = (1 - k)^2 / (SE - \frac{D}{N}). \tag{9}\]

It is easy to see that if analysts use the efficient weights \(\beta_u\), that is, if \(k = \beta_u = s / (s + h)\), then we have the BKLS model. However, previous empirical work (Chen and Jiang 2006; Zhang 2006; Kim et al. 2007) shows that the actual weight may deviate from the efficient weight (\(k \neq \beta_u\)).

When the actual weight \(k\) is not equal to the efficient weight, we have three unknown variables – \(h, s,\) and \(k\) – but only two equations (8) and (9). We therefore use the conditional characteristics of
forecasting error to come up with a third equation that establishes the relationship between the actual weight $k_{it}$ and the efficient weight $\beta_{it}$. Given an analyst’s forecasting strategy (equation (5)) and an efficient strategy (equation (3)), the expected forecast error is related to the public information in the following way.

$$E(f_{it} - y_i | z_i, q_{it}) = \frac{k_{it} - \beta_{it}}{k_{it}} (f_{it} - z_i),$$

(10)

where

$f_{it}$ is analyst $i$’s earnings forecast at time $t$,

$y_i$ is the actual earnings,

$z_i$ is the public information at time $t$,

$q_{it}$ is the private information held by analyst $i$ at time $t$,

$k_{it}$ is the actual weight of the private information used to form the earnings forecast, and

$\beta_{it}$ is the theoretical (rational) weight of the private information used to form the earnings forecast.

Equation (10) is identical to that used by Chen and Jiang (2006) to determine whether analysts overweight private information in forming their forecasts (i.e., whether $k_{it} - \beta_{it}$ is greater than zero). If $k_{it} = k$ and $\beta_{it} = \beta$ (i.e., if $\frac{s_{it}}{s_{it} + h_{it}}$ is constant over time), then we can take the unconditional expectation of equation (10) and obtain

$$\frac{k - \beta}{k} = \frac{E(f_{it} - y)(f_{it} - z_i))}{E((f_{it} - z_i)^2)} = \alpha.$$}

(11)
Here, $\alpha$ is a measure of the deviation in weighting from the efficient forecast, which we call the efficiency level measure. Jointly solving equations (4), (8), (9), and (11) allows us to compute the precision of public information ($h$), the precision of private information ($s$), and the actual weighting given to private information ($k$).

**Proposition 2**

If at time $T$ $s_{iT} = s, k_{iT} = k$ and $\beta_{iT} = \beta$, then we have

$$k = \frac{(SE - D/N + 2\alpha D) - \sqrt{(SE - D/N)^2 - 4\alpha^2 (SE - D/N)D}}{2\alpha (SE + D - D/N)},$$

$$s = k^2 / D,$$

$$h = (1-k)^2 / (SE - D/N).$$

Proposition 2 gives the formula to measure the information content in analyst forecasts $f_{iT}$, provided that we can observe the expected forecast dispersion $D$, the expected squared-forecast error $SE$, and the efficiency level measure $\alpha$. Proposition 2 also reveals the dynamic interactions among forecast dispersion ($D$), biased analyst weightings ($k$), the precision of public information ($h$) and the precision of private information ($s$).

To properly estimate the parameters in this equation, we need to consider how analysts update their forecasts. As private information may arrive at different times for different analysts, analysts make forecasts sequentially. At any moment, analysts can observe both the general public information and the forecasts made by their peer analysts. Therefore, the private information held by analysts making early forecasts becomes partially public, and is included in $f_{iT}$. 

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Clearly, not all analysts give their forecasts $f_{iT}$ at time $T$ simultaneously. Analysts may report their forecasts at different times, and have the option of revising their forecast after observing the forecasts of their peers. Some analysts choose to revise because new information has arrived, but some choose not to revise because they believe that their original forecast remains valid. However, we can reasonably assume that the last forecast made before time $T$ represents an analyst’s expectations of earnings at time $T$, as no new information has warranted a forecast revision. Therefore, even if the forecasts $f_{iT}$ are not made simultaneously at time $T$, we can reasonably assume that this is so. This assumption is also consistent with the BKLS model. Ivkovic and Jegadeesh (2004) express some concerns about this assumption, but Barron et al. (2008) empirically demonstrate that time variation in analyst forecasts does not affect the validity of the BKLS measure or its implications.

As in Barron et al. (1998), we use the sample dispersion $d$ as a proxy for the unconditional expectation and the sample squared-forecast error as a proxy for the unconditional expectation. The efficiency level measure $\alpha$ given in equation (11) relies on the public information $z_t$. Following Chen and Jiang (2006), we use the forecast consensus at time $t$ as a proxy for the public information available at time $t$. We run linear regression

$$(f_a - y) = a(f_a - z_t) + \eta$$

and use its ordinary least squares (OLS) estimation $\hat{\alpha}$ as the approximation for $\alpha$. This allows us to obtain estimates for $h$, $s$, and $k$.

IV. Sample Selection, Research Design, and Empirical Results

To estimate the information parameters in proposition 2 around earnings announcements, we consider the following windows.
We start with the 4\textsuperscript{th} quarter earnings announcement in the previous year and the subsequent four quarterly earnings announcements in the current year. We then divide the period between two quarterly announcements into two even periods. Periods 0, 2, 4, 6, and 8 represent the periods before quarterly earnings announcements, and periods 1, 3, 5, and 7 represent the periods after earnings announcements. In our analysis, we are interested in how the information environment changes between different periods (i.e., between periods 1 and 0, 3 and 2, 5 and 4, and 7 and 6).

We follow the steps outlined in the literature (Barron et al. 2002; Hui and Yeung 2007; Clement and Tse 2005; Yeung 2008) to extract the data for our analysis. Our sample includes firm-years from 1986 to 2007 that satisfy the following requirements.

1. Annual actual EPS data for the current year are available on the I/B/E/S database.

2. Analyst forecasts of annual EPS data for the current year are available on the I/B/E/S database.

3. Earnings announcement dates for all four quarters in the year and for the fourth quarter of the previous year are available from the Compustat Database.

4. The stock price is greater than $1 at the quarter end.

5. The price-deflated analyst forecast error is between -1 and 1.

6. The number of reporting days between two consecutive quarterly earnings is greater than two months and less than four months.
7. There are at least two analysts following the firm every quarter.

8. For the firm/year regression, there are at least twenty observations per firm/year.

9. For the matched sample analysis, the sample firm has at least two analyst forecasts in two consecutive periods.

The final sample includes 16,914 firm-years with 933,399 forecast observations. In our initial tests we do not require our sample to match across all nine forecast windows. However, in our robustness tests, we impose this restriction, as specified in Barron et al. (2002), and obtain a reduced sample of 3,476 firm-year observations.²

Equations (6) and (7) offer a formula for computing the forecast dispersion \(D\) and squared forecast error \(SE\). If an analyst makes multiple forecasts during any period, then we retain the latest forecast, as it contains the most updated information.³ To obtain the deviation in weight from the efficient weight \(\alpha\), we run regression (12). The left-hand variable \((f_{it} - y)\) is the forecast error and is measured by the difference between the forecasted earnings and the realized earnings. The independent variable \((f_{it} - z_t)\) is the difference between the forecasted earnings and the public information available at the time. Chen and Jiang (2006) suggest that it can be proxied by the difference between forecasted earnings and forecast consensus. We follow Chen and Jiang (2006) in constructing forecast consensus by computing it as a weighted average of all of the prevailing forecasts, with an

² Barron et al. (2002) use the data between 1986 and 1997 and have a sample size of 990. They only match the sample across two windows around the announcement (0-1, 2-3, 4-5, 6-7). In our analysis, we compare the information environment for all windows (0-1, 1-2, 2-3 ... 7-8) between 1986 and 2007.

³ Barron et al. (2002) use the last forecast before an earnings announcement and the first forecast after an earnings announcement for multiple forecasts. We also analyze our data using their definition, and find results consistent with those reported in their paper.
inverse-weighting scheme\(^4\) applied to assign higher weights to more recent forecasts because they contain more updated information.\(^5\) We also try the simple average approach to compute the consensus and obtain similar results to those achieved using the inverse-weighting scheme. We report the summary statistics for the main variables in Table 1. Both the forecast values \((f)\) and the forecast consensus \((x)\) are slightly higher than the actual EPS values \((y)\), indicating some sort of over-optimism in the analyst forecasts. The mean forecast error \((f-y)\) amounts to 8 cents and the median forecast error is close to 0. The mean deviation from the consensus \((f-x)\) is around minus 2 cents. All of these variables are skewed with large outliers.\(^6\) Table 1 also reports the statistics after deflating the variable \((d(f), d(y), d(x), d(f-x), d(f-y))\) by the quarter-end stock price. In general, the deflated variables are less skewed and the overall characteristics of the sample remain unchanged.

**Insert Table 1 Here**

We next modify equation (12) to incorporate the walkdown-walkup patterns of analyst earnings forecasts (Krishnan et al. 2007; Cotter et al. 2006; Ciccone 2005) by including a time variable \(t\). \(t\) measures the distance between the forecast and the current year 4\(^{th}\) quarter earnings announcement. As indicated in the timeline at the beginning of section IV, \(t\) equals 0, 1 ... 8. Furthermore, we know that the information set in the period after the earnings announcements differs from that in the period before the earnings announcements, and thus include a dummy variable “post” that equals 1 if the

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\(^4\) The weighting scheme is fully explained in Chen and Jiang (2006). Briefly, it is computed as 
\[ w_n = \frac{(1/d_n)}{(\sum_{n=1}^{N} (1/d_n))} \]
where \(n = 1, ... , N\) is the number of prevailing forecasts and \(d_n\) represents the number of days before the current forecast date.

\(^5\) Following Chen and Jiang (2006), we use all of the forecasts for the same firm quarter issued at least one day before the current forecast to compute the consensus.

\(^6\) We obtain qualitatively similar results (not reported) when we remove the outliers from the sample.
forecast appears in the period after an earnings announcement and 0 otherwise. Our revised model of Chen and Jiang (2006) then becomes

\[ f_{it} - \gamma = (\alpha_0 + \alpha_1 \text{post} + \alpha_2 t)(f_{it} - z_i) + \eta. \]

The results for equation (13) are reported in Table 2. Models 1 and 2 use the raw variables and models 3 and 4 use the deflated measures. All of the coefficients are significant at the 1% level. In models 1 and 2, \( \alpha_0 \) (the coefficients for \( f_{it}-z_i \)) are positive, suggesting that analysts place a higher than efficient weight on private information, a result that is consistent with the findings of Chen and Jiang (2006). The coefficients for the cross term between the Post Earnings Dummy and Deviation from Consensus (\( \text{post} \times (f-z) \)) are also positive, which shows that in the period right after earnings announcements analysts place a higher weight on private information. The negative coefficients for the cross term between the time variable and Deviation from Consensus (\( t \times (f-z) \)) indicate that analysts gradually reduce the weights accorded to private information as they approach the fourth quarter earnings announcements. Models 3 and 4 conduct similar tests using deflated measures to control for the scale effect in the sample. A comparison of models 1-2 and 3-4 shows their results to be qualitatively similar for the coefficients of \( f_{it}-z_i \) and \( \text{post} \times (f-z) \), but that the coefficient estimates for the cross term between the time variable and Deviation from Consensus \( t \times (f-z) \) differ greatly.

Insert Table 2 Here

Chen and Jiang (2006) question the usefulness of using deflated variables to control the scale effect, because the scale factor can introduce different biases. As there is no theoretical support for one

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7 We exclude forecasts made on the day immediately after an earnings announcement in the regression because the consensus measure fails to properly account for the available public information at that time.

8 This is the case because in equation (11) \( \alpha = (k-\beta)/k \). If the weight is optimal, then \( \alpha \) should be 0, as \( k = \beta \). If \( \alpha > 0 \), then a larger than optimal weight is placed on private information.
approach over the other, we conduct firm-year regressions to estimate the model in equation (13). As these regressions are run for each company separately, we do not have to worry about the scale effect for different firms. The only downside is that we have to omit firms with too few observations to run a regression analysis, although only a small number of firms are dropped due to this data constraint. We also remove firm or year observations with $a_0$ (coefficients for $f_{it}$) more than four standard deviations away from the mean.\(^9\) We run 16,914 separate regressions and retrieve the coefficients for each test. A summary of the regression results is reported in Table 3. The coefficients appear to be qualitatively consistent with those reported for models 3 and 4 in Table 2.

*Insert Table 3 Here*

After obtaining the estimates for $a_0$, $a_1$, and $a_2$, we can jointly solve equations (4), (8), (9), and (11) for $h$, $s$, $k$, and $\beta$. In Table 4 we present the parameter estimates together with the BKLS estimates to illustrate the difference between the two approaches. As mentioned in our earlier discussion, the BKLS measure assumes that analysts use the optimal weight when making forecasts, and constructs their weight (BKLS-$\beta$) for private information as $\frac{s}{s + h}$. Using the equation presented at the beginning of section III, we can compute the BKLS measure for $\beta$, $s$, and $h$. In Table 4, we also take the natural logarithm of $s$, BKLS-$s$, $h$, and BKLS-$h$ for easy comparison. It can be seen that the BKLS measure largely overestimates the efficient weight $\beta$ and the precision of private information $s$ and underestimates the precision of public information $h$. By overestimating $\beta$, BKLS conclude that there is a significant increase in idiosyncratic information after earnings announcements. A critical aspect of our analysis is the measure for the actual weight used by analysts (i.e., $k$). We show that $k$ (mean = 0.260, median = 0.076) is higher than the efficient weight $\beta$ (mean = 0.134, median = 0.042), but significantly less than the BKLS

\(^9\) The results are qualitatively similar when these outliers are retained.
- $\beta$ (mean = 0.377, median = 0.218). Our results are consistent with the literature that suggests that analysts place a larger than efficient weight on private information. By explicitly extracting such bias from the forecast dispersion we can better recognize the changes in public and private information contained in forecasts.

**Insert Table 4 Here**

We report the incremental changes in $\beta$ for different periods in Table 5. We also report the BKLS-$\beta$ for comparison. Interestingly, after earnings announcements in periods 1, 3, 5, and 7, the proportion of private information ($\beta$) drops significantly. We also replicate the results in Barron et al. (2002) using the measure reported in their paper, and similarly find that the proportion of private information appears to increase significantly after earnings announcements, with the trend continuing into the last quarter of the year.

**Insert Table 5 Here**

Figure 1 plots the $\beta$ and $k$ estimates (median value) from our model and the $\beta$ value from the BKLS model. Graphically, we can see that BKLS-$\beta$ increases rapidly from periods 0 to 8, with a much greater increase in periods 6, 7, and 8 as companies disclose their earnings for the last quarter and for the whole fiscal year. However, we do not observe any noticeable changes in $\beta$ using our model. We do, however, find a steady increase in $k$ between periods 0 and 8. This suggests that the observed upward trend in BKLS-$\beta$ is driven more by the upward trend in $k$ than the increase in the proportion of private information.

**Insert Figure 1 Here**
V. Robustness Tests

We conduct a series of robustness tests to ensure the consistency of our results. As mentioned in our previous discussions, we try alternative measures of forecast consensus and find similar results to those reported in this paper. We also remove the extreme values in our sample and obtain consistent results. In many cases, our results are even stronger after removing the outliers. We have reported the estimates of \( \alpha_0 \) using the firm-year approach in Table 3. Although not reported here, we also try the pooled sample approach and the pooled sample approach with scale adjustment to measure \( \alpha_0 \). Our subsequent measures of \( k \) and \( \beta \) remain qualitatively unchanged from those reported in the paper.

In Table 6 we report a robustness test using the sample selection criteria stated in Barron et al. (2002). Specifically, the sample includes only firms with forecasts made by the same analyst before and after an earnings announcement. Pre- and post-announcement period forecasts must be available from at least two analysts for each of the four previous earnings announcements. Basically, forecasts made following earnings announcements are matched with forecasts made before earnings announcements before the parameters are estimated. This approach reduces our sample size to 359,617 observations and 3,476 firm-year observations. Barron et al. (2002) argue that the construction of the sample following this approach ensures a clean and unbiased comparison of information changes before and after earnings announcements.

Insert Table 6 Here

We report the mean tests in Table 6 for the changes in \( \beta \), \( h \) and \( s \) in two consecutive periods (the median tests give similar results). We see significant decreases in \( \beta \) from period 0 to 1, from period 2 to 3, from period 4 to 5, and from period 6 to 7. The changes for the other periods are significantly

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\(^{10}\) We do not report the results of some of the robustness tests to save space. They are available from the authors upon request.
positive. These results differ greatly from the results reported in Barron et al. (2002), who observe a large and significant increase in $\beta$. We also observe biases in the BKLS measure with respect to $\Delta s$ and $\Delta h$. We notice that the changes in both private and public information are highly significant for two neighboring periods. More importantly, we notice that the BKLS measure greatly overstates $\Delta s$ and understates $\Delta h$. Such biases contribute to the overstatement of $\beta$ ($i.e. \frac{s}{s + h}$). Interestingly, our findings echo the concern of Hui and Yeung (2007) that the observed increase in the BKLS measure of private information is largely due to the usage of better and greater public information, rather than the additional production of private information by analysts.

VI. Conclusion

Ramnath et al. (2008) provide a comprehensive review of the financial analyst forecasting literature and conclude that one of the most promising areas for future research is the search for greater insight into the analyst decision process. They suggest that “research clarifying the distinction between analysts’ roles as interpreters of public information and as developers of private information” is crucial to our understanding of the literature. We attempt to tackle this issue by providing a theoretical and empirical examination of the information environment after earnings announcements.

The seminal work of Barron et al. (1998) has found numerous applications in recent years. Their thorough yet succinct approach has made it possible for researchers to examine the information environment in various situations. We generalize the popular BKLS measure by explicitly considering analyst bias in forming earnings forecasts. Applying our measure to earnings announcements, we find that analysts overweight private information when producing earnings forecast revisions after quarterly earnings announcements. We further find that the proportion of private information in post-announcement forecasts experiences a significant decrease and the proportion of public information a
significant increase. Our results are consistent with the view that earnings announcements reduce information uncertainty and discourage analysts from obtaining private information. They are also consistent with the overconfident behavior of analysts, who are inclined to “irrationally” overweight their private information. Finally, the less than optimal weight accorded to public information is consistent with the observed post-earnings drift that occurs when analysts downplay the importance of public information in forecasting earnings.

As Barron et al. (2002) point out, “the question of whether public accounting disclosures trigger significant idiosyncratic information is central in understanding the role of accounting disclosures.” We build our model upon the BKLS measure and reveal results that differ from those in recent papers that find a surge of idiosyncratic risk after earnings announcements. By taking into consideration the behavioral biases in analyst forecasts, we come up with an approach that properly accounts for both the weight and the level of information contained in a forecast.

Our model and research design outline how the weight and the level of public and private information can be decomposed, and suggest that previous studies that infer the level of idiosyncratic information may be biased if they failed to properly account for the weighting bias in forecasts. Our model can also be applied to the study of post-earnings announcement drift if the change in public information and its associated weight is considered in the forecasts.
References:


Kim, C., S. Lee, and C. Pantzalis. 2007. Analyst forecast inefficiency in reaction to earnings news: Cognitive bias vs. economic incentives, Working Paper, City University of Hong Kong and University of South Florida.


Appendix:

Proof of proposition 1:

Define \( V = \frac{1}{N} \sum_{i=1}^{N} V_i = \frac{1}{N} \sum_{i=1}^{N} E(f_{IT} - y)^2 \);

\[
C = \frac{1}{N} \sum_{i=1}^{N} C_i = \frac{1}{N} \sum_{i=1}^{N} \sum_{j \neq i}^{N} E(f_{IT} - y)(f_{IT} - y).
\]

But \( f_{IT} = kq_{IT} + (1 - k)z_T \),

\[
q_{IT} = y + u_{IT},
\]

\[
z_T = y + \varepsilon_T.
\]

We have \( E(f_{IT} - y)^2 = \frac{k^2}{s} + \frac{(1 - k)^2}{h} \),

\[
E(f_{IT} - y)(f_{JT} - y) = \frac{(1 - k)^2}{h},
\]

Hence \( V = \frac{k^2}{s} + \frac{(1 - k)^2}{h} \),

\[
C = \frac{(1 - k)^2}{h}.
\]

On the other hand, by lemma 1 of BKLS, we have

\( D = V - C, \)

\( SE = C + \frac{D}{N}. \)

Hence we can solve \( s \) and \( h \) using \( D \) and \( SE \):

\[
s = \frac{k^2}{D},
\]

\[
h = \frac{(1 - k)^2}{(SE - \frac{D}{N})}.
\]
Table 1: Descriptive Statistics
The sample period is between 1986 and 2007. Forecast value \((f)\) and actual value \((y)\) are annual earnings per share forecasts and actual value reported in I/B/E/S. Forecast consensus \((x)\) are computed as a weighted average of all prevailing forecasts and inverse-weighting scheme is applied to assign higher weights to more recent forecasts. Forecast error \((f-y)\) is measured as the difference between forecast value and actual value. Deviation from consensus \((f-x)\) is the difference between forecast value and forecast consensus. We divide the original variables by their corresponding quarter end stock prices to construct the deflated variables \(d(f), d(y), d(x), d(f-x)\) and \(d(f-y)\).

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Min</th>
<th>Max</th>
<th>25 percentile</th>
<th>75 percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>(f)</td>
<td>1.533</td>
<td>1.155</td>
<td>2.451</td>
<td>-61.300</td>
<td>225.000</td>
<td>0.510</td>
<td>2.100</td>
</tr>
<tr>
<td>(y)</td>
<td>1.449</td>
<td>1.093</td>
<td>2.535</td>
<td>-52.600</td>
<td>198.000</td>
<td>0.440</td>
<td>2.050</td>
</tr>
<tr>
<td>(x)</td>
<td>1.550</td>
<td>1.170</td>
<td>2.436</td>
<td>-59.100</td>
<td>225.000</td>
<td>0.525</td>
<td>2.120</td>
</tr>
<tr>
<td>(f-y)</td>
<td>0.084</td>
<td>0.000</td>
<td>0.854</td>
<td>-27.480</td>
<td>48.880</td>
<td>-0.070</td>
<td>0.125</td>
</tr>
<tr>
<td>(f-x)</td>
<td>-0.017</td>
<td>0.000</td>
<td>0.456</td>
<td>-42.500</td>
<td>44.750</td>
<td>-0.047</td>
<td>0.030</td>
</tr>
<tr>
<td>(d(f))</td>
<td>0.040</td>
<td>0.038</td>
<td>0.126</td>
<td>-9.200</td>
<td>7.725</td>
<td>0.017</td>
<td>0.063</td>
</tr>
<tr>
<td>(d(y))</td>
<td>0.033</td>
<td>0.035</td>
<td>0.130</td>
<td>-8.743</td>
<td>6.798</td>
<td>0.015</td>
<td>0.060</td>
</tr>
<tr>
<td>(d(x))</td>
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<td>0.038</td>
<td>0.124</td>
<td>-8.857</td>
<td>7.725</td>
<td>0.017</td>
<td>0.064</td>
</tr>
<tr>
<td>(d(f-x))</td>
<td>0.007</td>
<td>0.000</td>
<td>0.047</td>
<td>-0.994</td>
<td>1.000</td>
<td>-0.002</td>
<td>0.005</td>
</tr>
<tr>
<td>(d(f-y))</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.022</td>
<td>-1.950</td>
<td>2.023</td>
<td>-0.001</td>
<td>0.001</td>
</tr>
<tr>
<td># of Forecasts per firm/year</td>
<td>82.765</td>
<td>67</td>
<td>56.547</td>
<td>20</td>
<td>379</td>
<td>41</td>
<td>109</td>
</tr>
<tr>
<td># of Analysts per firm/year</td>
<td>6.818</td>
<td>5</td>
<td>5.016</td>
<td>2</td>
<td>39</td>
<td>3</td>
<td>9</td>
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<tr>
<td>Total number of observations</td>
<td>933399</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of firm/year observations</td>
<td>16914</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 2: Regression Results

The regression model is \((f_t - y) = (\alpha_0 + \alpha_1 post + \alpha_2 t)(f_t - z_t) + \eta\). The dependent variable \((f_t - y)\) is forecast error and it is computed as the difference between forecast value and actual value. The independent variable \((f_t - z_t)\) is the difference between the forecast and the public information available at time \(t\). It is proxied by the deviation from consensus and is equal to the difference between forecast value and consensus value. Post dummy equals 1 if the forecast is made in the period right after earnings announcement and 0 otherwise. Time variable \(t\) measures the distance of the forecast with respect to the 4th quarter earnings announcement in the current year. Models 1 and 2 use the raw variables. Models 3 and 4 use the variables deflated by the quarter-end stock price.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
<th>Model 4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>t-value</td>
<td>Coefficient</td>
<td>t-value</td>
<td>Coefficient</td>
<td>t-value</td>
<td>Coefficient</td>
<td>t-value</td>
</tr>
<tr>
<td>(f-z)</td>
<td>0.218</td>
<td>51.75***</td>
<td>0.168</td>
<td>61.74***</td>
<td>0.160</td>
<td>36.62***</td>
<td>0.221</td>
<td>74.78***</td>
</tr>
<tr>
<td>post*(f-z)</td>
<td>0.055</td>
<td>14.23***</td>
<td>0.049</td>
<td>12.68***</td>
<td>0.051</td>
<td>11.68***</td>
<td>0.061</td>
<td>14.12***</td>
</tr>
<tr>
<td>t*(f-z)</td>
<td>-0.012</td>
<td>-15.64***</td>
<td>0.017</td>
<td>19.31***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adj (R^2)</td>
<td>0.011</td>
<td></td>
<td>0.011</td>
<td></td>
<td>0.015</td>
<td></td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>F-Value</td>
<td>3415.92***</td>
<td></td>
<td>5000.29***</td>
<td></td>
<td>4608.49***</td>
<td></td>
<td>6723.56***</td>
<td></td>
</tr>
</tbody>
</table>

***: significant at the level of 1%
Table 3: Summary of Regression Results Using the Firm/Year Sample
The regression model is \( (f_i - y) = (\alpha_0 + \alpha_p \text{post} + \alpha_t)(f_i - z_i) + \eta \). The model is run for every firm in every year from 1986 to 2007 separately. The dependent variable \( (f_i - y) \) is forecast error and is computed as the difference between forecast value and actual value. The independent variable is deviation from consensus \( (f_i - z) \) and is equal to the difference between forecast value and consensus value. Post dummy equals 1 if the forecast is made in the period right after earnings announcement and 0 otherwise. Time variable \( t \) measures the distance of the forecast with respect to the 4th quarter earnings announcement in the current year.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>25 percentile</th>
<th>75 percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>f-z</td>
<td>0.016</td>
<td>0.426</td>
<td>1.887</td>
<td>-11.613</td>
<td>11.560</td>
<td>-0.411</td>
<td>0.854</td>
</tr>
<tr>
<td>post*(f-z)</td>
<td>0.148</td>
<td>0.079</td>
<td>1.631</td>
<td>-56.218</td>
<td>27.225</td>
<td>-0.342</td>
<td>0.574</td>
</tr>
<tr>
<td>t*(f-z)</td>
<td>0.061</td>
<td>0.021</td>
<td>0.336</td>
<td>-6.085</td>
<td>3.457</td>
<td>-0.065</td>
<td>0.146</td>
</tr>
<tr>
<td># observations per firm/year</td>
<td>55.187</td>
<td>42</td>
<td>42.013</td>
<td>20</td>
<td>379</td>
<td>29</td>
<td>68</td>
</tr>
<tr>
<td>Adj R²</td>
<td>0.257</td>
<td>0.190</td>
<td>0.217</td>
<td>0.000</td>
<td>0.998</td>
<td>0.084</td>
<td>0.382</td>
</tr>
</tbody>
</table>
Table 4: Parameter Estimates
The analyst’s best conditional estimate of $y$ (actual earnings), given $z_i$ (public information) and $q_{it}$ (private information), is formed by Bayes’ rule: $f_{it} = E(y|z_i, q_{it}) = \beta_i q_{it} + (1- \beta_i) z_i$, where $\beta_i = s_{iti} / (h_{iti} + s_{iti})$ is the efficient weight, which minimizes the mean-squared error of forecast. $s$ is the precision of private information. $H$ is the precision of public information. BKLS-$\beta$, BKLS-$s$ and BKLS-$h$ are the weight, the precision of private information and the precision of public information based on the BKLS model respectively. $k$ is the actual but biased weight used by analysts when forming earnings expectations.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean</th>
<th>Median</th>
<th>Std Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
<th>1 percentile</th>
<th>99 percentile</th>
<th>25 percentile</th>
<th>75 percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.134</td>
<td>0.042</td>
<td>0.195</td>
<td>0.000</td>
<td>1.000</td>
<td>0.000</td>
<td>0.849</td>
<td>0.001</td>
<td>0.189</td>
</tr>
<tr>
<td>BKLS-$\beta$</td>
<td>0.377</td>
<td>0.218</td>
<td>0.373</td>
<td>0.000</td>
<td>1.000</td>
<td>0.000</td>
<td>1.000</td>
<td>0.042</td>
<td>0.718</td>
</tr>
<tr>
<td>Ln($s$)</td>
<td>-1.409</td>
<td>0.793</td>
<td>8.106</td>
<td>-40.180</td>
<td>17.791</td>
<td>-23.740</td>
<td>10.280</td>
<td>-3.848</td>
<td>4.069</td>
</tr>
<tr>
<td>Ln(BKLS-$s$)</td>
<td>2.100</td>
<td>2.703</td>
<td>4.981</td>
<td>-37.201</td>
<td>18.749</td>
<td>-16.380</td>
<td>11.080</td>
<td>-0.327</td>
<td>5.323</td>
</tr>
<tr>
<td>Ln(BKLS-$h$)</td>
<td>1.897</td>
<td>3.158</td>
<td>5.601</td>
<td>-31.854</td>
<td>20.721</td>
<td>-17.010</td>
<td>10.430</td>
<td>0.529</td>
<td>5.194</td>
</tr>
<tr>
<td>$k$</td>
<td>0.260</td>
<td>0.076</td>
<td>0.350</td>
<td>0.000</td>
<td>1.000</td>
<td>0.000</td>
<td>1.000</td>
<td>0.006</td>
<td>0.385</td>
</tr>
</tbody>
</table>
Table 5: Changes in the Proportion of Idiosyncratic Information in the Information Set (Full Sample)

This table reports the results using the full sample. The analyst's best conditional estimate of $y$ (actual earnings), given $z_t$ (public information) and $q_{it}$ (private information), is formed by Bayes' rule: $f(y|z_t, q_{it}) = \beta_i q_{it} + (1-\beta_i) z_t$, where $\beta_i = s_i/(h_i + s_i)$ is the efficient weight that minimizes the mean-squared error of forecast. $s$ is the precision of private information. $h$ is the precision of public information. BKLS-$\beta$ is the weight based on the BKLS model. We find the midpoints between two quarterly earnings announcements and divide them into two periods for each interval between two quarterly earnings announcements. Altogether, we have eight periods where period 0 is the window prior to the 4th quarter earnings announcement in the prior year and period 8 is the window prior to the 4th quarter earnings announcement in the current year.

<table>
<thead>
<tr>
<th>Time</th>
<th>Mean</th>
<th>diff</th>
<th>t value</th>
<th>Median</th>
<th>diff</th>
<th>Z value</th>
<th>Mean</th>
<th>diff</th>
<th>t value</th>
<th>Median</th>
<th>diff</th>
<th>Z value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.115</td>
<td>-0.008</td>
<td>-3.87***</td>
<td>0.039</td>
<td>-0.009</td>
<td>-6.16***</td>
<td>0.285</td>
<td>0.002</td>
<td>0.53</td>
<td>0.106</td>
<td>-0.001</td>
<td>-0.17</td>
</tr>
<tr>
<td>1</td>
<td>0.107</td>
<td>-0.008</td>
<td>-3.87***</td>
<td>0.030</td>
<td>-0.009</td>
<td>-6.16***</td>
<td>0.287</td>
<td>0.019</td>
<td>4.50***</td>
<td>0.131</td>
<td>0.025</td>
<td>6.18***</td>
</tr>
<tr>
<td>2</td>
<td>0.129</td>
<td>0.022</td>
<td>10.24***</td>
<td>0.045</td>
<td>0.015</td>
<td>13.54***</td>
<td>0.306</td>
<td>0.019</td>
<td>4.50***</td>
<td>0.131</td>
<td>0.025</td>
<td>6.18***</td>
</tr>
<tr>
<td>3</td>
<td>0.114</td>
<td>-0.015</td>
<td>-6.61***</td>
<td>0.035</td>
<td>-0.010</td>
<td>-8.84***</td>
<td>0.320</td>
<td>0.014</td>
<td>3.12***</td>
<td>0.146</td>
<td>0.015</td>
<td>4.22***</td>
</tr>
<tr>
<td>4</td>
<td>0.146</td>
<td>0.032</td>
<td>14.22***</td>
<td>0.057</td>
<td>0.022</td>
<td>16.66***</td>
<td>0.353</td>
<td>0.033</td>
<td>7.93***</td>
<td>0.193</td>
<td>0.047</td>
<td>9.53***</td>
</tr>
<tr>
<td>5</td>
<td>0.126</td>
<td>-0.020</td>
<td>-8.77***</td>
<td>0.037</td>
<td>-0.020</td>
<td>-13.92***</td>
<td>0.381</td>
<td>0.028</td>
<td>6.51***</td>
<td>0.231</td>
<td>0.038</td>
<td>6.55***</td>
</tr>
<tr>
<td>6</td>
<td>0.167</td>
<td>0.041</td>
<td>16.78***</td>
<td>0.069</td>
<td>0.032</td>
<td>16.90***</td>
<td>0.441</td>
<td>0.060</td>
<td>13.76***</td>
<td>0.343</td>
<td>0.112</td>
<td>14.53***</td>
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<td>7</td>
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<td>-0.024</td>
<td>-9.07***</td>
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<td>-0.036</td>
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<td>0.053</td>
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<td>0.447</td>
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<tr>
<td>8</td>
<td>0.166</td>
<td>0.023</td>
<td>8.05***</td>
<td>0.043</td>
<td>0.010</td>
<td>5.74***</td>
<td>0.518</td>
<td>0.024</td>
<td>5.17***</td>
<td>0.500</td>
<td>0.053</td>
<td>4.37***</td>
</tr>
</tbody>
</table>

***: significant at the level of 1%
Table 6: Changes in the Proportion of Idiosyncratic Information in the Information Set (Matched Sample)

This table reports results using the matched sample. To be included in the analysis, a firm needs to have forecasts made by the same analyst before and after an earnings announcement. Pre- and post-announcement period forecasts must be available from at least two analysts for each of the four prior earnings announcements. The analyst’s best conditional estimate of y (actual earnings), given $z_t$ (public information) and $q_{it}$ (private information), is formed by Bayes’ rule: $f_{it} = E(y|z_t, q_{it}) = \beta_{it} q_{it} + (1- \beta_{it}) z_t$, where $\beta_{it} = s_{it} / (h_{it} + s_{it})$ is the efficient weight, which minimizes the mean-squared error of forecast. $s$ is the precision of private information. $h$ is the precision of public information. BKLS-$\beta$, BKLS-$s$ and BKLS-$h$ are the weight, the precision of private information and the precision of public information based on the BKLS model respectively. We find the midpoints between two quarterly earnings announcements and divide them into two periods for each interval between two quarterly earnings announcements. Altogether, we have eight periods where period 0 is the window prior to the 4th quarter earnings announcement in the prior year and period 8 is the window prior to the 4th quarter earnings announcement in the current year. $\Delta$ measures the mean differences in specific variables between two periods.

<table>
<thead>
<tr>
<th>Period</th>
<th>$\Delta \beta$</th>
<th>t value</th>
<th>$\Delta$BKLS-$\beta$</th>
<th>t value</th>
<th>$\Delta s$</th>
<th>t value</th>
<th>$\Delta$BKLS-$s$</th>
<th>t value</th>
<th>$\Delta h$</th>
<th>t value</th>
<th>$\Delta$BKLS-$h$</th>
<th>t value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-0</td>
<td>-0.010</td>
<td>-3.48***</td>
<td>0.006</td>
<td>1.13</td>
<td>-0.393</td>
<td>-2.76***</td>
<td>0.358</td>
<td>5.03***</td>
<td>0.383</td>
<td>13.35***</td>
<td>0.149</td>
<td>1.69*</td>
</tr>
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<td>7.64***</td>
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</tbody>
</table>

***: significant at the level of 1%; **: significant at the level of 5%; *: significant at the level of 10%
Figure 1
The analyst’s best conditional estimate of $y$ (actual earnings), given $z_t$ (public information) and $q_{it}$ (private information), is formed by Bayes’ rule: $f_{it} = E(y|z_t, q_{it}) = \beta_{it}q_{it} + (1-\beta_{it})z_t$, where $\beta_{it} = s_{it}/(h_{it} + s_{it})$ is the efficient weight, which minimizes the mean-squared error of forecast. $s$ is the precision of private information. $h$ is the precision of public information. BKLS-$\beta$ is the weight based on the BKLS model. $k$ is the actual but biased weight used by analysts when forming expectation.
Founded in 1892, the University of Rhode Island is one of eight land, urban, and sea grant universities in the United States. The 1,200-acre rural campus is less than ten miles from Narragansett Bay and highlights its traditions of natural resource, marine and urban related research. There are over 14,000 undergraduate and graduate students enrolled in seven degree-granting colleges representing 48 states and the District of Columbia. More than 500 international students represent 59 different countries. Eighteen percent of the freshman class graduated in the top ten percent of their high school classes. The teaching and research faculty numbers over 600 and the University offers 101 undergraduate programs and 86 advanced degree programs. URI students have received Rhodes, Fulbright, Truman, Goldwater, and Udall scholarships. There are over 80,000 active alumnae.

The University of Rhode Island started to offer undergraduate business administration courses in 1923. In 1962, the MBA program was introduced and the PhD program began in the mid 1980s. The College of Business Administration is accredited by The AACSB International - The Association to Advance Collegiate Schools of Business in 1969. The College of Business enrolls over 1400 undergraduate students and more than 300 graduate students.

Mission

Our responsibility is to provide strong academic programs that instill excellence, confidence and strong leadership skills in our graduates. Our aim is to (1) promote critical and independent thinking, (2) foster personal responsibility and (3) develop students whose performance and commitment mark them as leaders contributing to the business community and society. The College will serve as a center for business scholarship, creative research and outreach activities to the citizens and institutions of the State of Rhode Island as well as the regional, national and international communities.

The creation of this working paper series has been funded by an endowment established by William A. Orme, URI College of Business Administration, Class of 1949 and former head of the General Electric Foundation. This working paper series is intended to permit faculty members to obtain feedback on research activities before the research is submitted to academic and professional journals and professional associations for presentations.

An award is presented annually for the most outstanding paper submitted.