Firm Size and the Benefit of Analysts' Heterogeneous Interpretations of Public Disclosures

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Abstract

I use forecasts of active analysts to examine the relationship between firm size and both the precision of pre-announcement information and new information triggered by earnings announcements. I find that analysts have more precise pre-announcement information for larger firms. Consistent with the predictions of Indjejikian's (1991) model, I also document that there are relatively more heterogeneous interpretations of earnings announcements in the forecasts revisions for larger firms after earnings announcements. This result is shown to be related to the association between firm size and the benefits of aggregating individual forecasts. The results are consistent with analysts acting as information intermediaries (Schipper 1991) who process financial accounting disclosures into privately inferred information, and with this activity being more prevalent where the demand for such information is likely to be greatest, that is for larger firms.

JEL classification: G14; G24.

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1. Introduction

This study examines the relation between firm size (i.e., market capitalization) and the information contained in analysts' earnings forecast revisions around (prior) earnings announcements. More specifically, I investigate the relationship between firm size and the levels of both individual analysts' common and idiosyncratic (uniquely private) pre-announcement information. Related to this association between firm size and the level of the precision of analysts' pre-announcement information, I also test for an association between firm size and the changes in analysts' information following earnings announcement. Using predictions from Indjejikian's (1991) model, which incorporates costly interpretations of public disclosures, I predict that there will be more heterogeneity in the information incorporated into forecast revisions after earnings announcements for larger firms.

Recent evidence of Barron, Byard and Kim (2002b) points to significance private information being triggered by active analysts surrounding financial report releases. For a sample of actively-updating analysts, they show that the release of most of individual analysts' idiosyncratic (uniquely private) information is triggered in the periods following financial report releases. They interpret this finding as evidence that, in part, analysts act as information intermediaries who process public accounting information into idiosyncratic information for market participants (Schipper 1991). If indeed analysts do fulfill this role, it should be more evident when the demand for such information increases. I contend that this is likely to be the case for larger firms.

Like Barron et al. (2002b), I use forecasts from actively updating analysts. I base my examination of a firm's information environment upon a study of the information reflected in these forecasts, and use the model of Barron, Kim, Lim and Stevens (1998) (hereafter, BKLS) to examine this information.[1] Use of the BKLS forecast approach contrasts with the existing

[1] This approach does not require that analysts' incentives exactly correspond to those of investors. Rather, it implicitly assumes that to some degree analysts respond to the same private information acquisition incentives as

market-based evidence concerning the relationship between firm size and firms' pre-announcement information. The BKLS forecast approach involves the use of observable characteristics of analysts' forecasts, namely, the squared error in the mean forecast and forecasts dispersion, together with the number of analysts' forecasts to infer the underlying properties of analysts' information. BKLS show how one can estimate the precision of individual analysts' common and idiosyncratic information from these observable characteristics of their forecasts.

Using the BKLS model, I measure the precision of individual analysts' common and idiosyncratic information prior to earnings announcements, and changes in this information after financial report releases. Consistent with prior market-based studies (e.g., see Atiase 1985; Freeman 1987; Bhushan 1989a), I find that the total amount (precision) of individual analysts' pre-announcement information increases with firm size. I also report direct evidence that the idiosyncratic (uniquely private) component of individual analysts' pre-disclosure information increases with firm size. Using Indjejikian's (1991) model, I then predict that there will be more demand for heterogeneous interpretations of earnings announcements in the forecast revisions for larger firms after earnings announcements. This arises from the greater demand for the risk-sharing benefits of such heterogeneous interpretations for these firms. Consistent with the predictions of Indjejikian's model, I find that there is a greater increase in the amount (precision) of new idiosyncratic (uniquely private) information contained in individual forecasts for larger firms after earnings announcements.

Finally, consistent with the risk sharing benefits of greater heterogeneity in the forecasts for larger firms, I also demonstrate that there is an increase in likelihood that the mean forecast is superior (more accurate) then any individual forecast for larger firms, compared to smaller firms. Thus, I find that the benefits of aggregating individual forecasts to generate more accurate summary earnings expectation estimates are related to firm size, not only because of the greater

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investors. This seems a reasonable assumption if analysts demand for information is, to a larger degree, derived from that of their investment clients (e.g., see Fischer and Verrecchia 1998). See also Botosan and Harris (2001) and Barron et al. (2002a, 2002b) for examples of recent empirical studies using the BKLS model.

number of forecasts available for these firms, but also because these individual forecasts each contain relatively more heterogeneous information (i.e., there is a lower level of consensus among individual analysts, or across-analyst correlation in forecast errors).

My results confirm the theoretical implications of prior market-based evidence (Atiase 1985) by demonstrating that the change in analysts' information following a financial report release relative to the total level of informedness following the announcement is decreasing in firm size.[2] I also find that after a financial report release, the precision of individual analysts' information increases *more* for larger firms than smaller firms, which is especially apparent for the precision of individual analysts' idiosyncratic information. I also demonstrate that the changes in the nature of actively updating analysts' information around earnings announcements are different for larger and smaller firms. Specifically, there is greater heterogeneity in the new information triggered by earnings announcement for these analysts for larger firms. This informational difference has implications for risk-sharing among short-horizon investors, and also has practical implications for understanding the informational benefits from aggregating informationally diverse forecasts from different individual analysts.

The remainder of this paper is organized as follows. Section 2 discusses the BKLS framework. Section 3 discusses related research and our expectations based upon this research. Section 4 outlines our test design and sample selection procedures in applying the BKLS framework. Section 5 describes the empirical results, and section 6 concludes with a discussion of its implications.

2. Overview of the BKLS Model

BKLS show that, under certain assumptions, one can express the average precision of individual analysts' common (h) and idiosyncratic (s), or uniquely private, information in terms

[2] In a model of rational trade, Kim and Verrecchia (1991) demonstrate that the price reaction to a public announcement is proportional to: $\frac{\Delta k}{k1 + \Delta k}$, where *k1* is the level of pre-announcement informedness (the precision of pre-announcement information), and Δk is the change in informedness as a result of the earnings announcement (see Kim and Verrecchia 1991; Proposition 1; p. 311).

of observable characteristics of analysts' forecasts. The BKLS measures of h and s are principally based upon the assumption that analysts make the most accurate forecasts they can, and that forecasts are of equal precision across analysts.[3]

BKLS model a setting where N financial analysts forecast earnings (y). Individual analysts observe common information (of precision h) and an idiosyncratic (or uniquely private) signal, $z_i = y + \varepsilon_i$. Each ε_i is independent of all other variables and is normally distributed with mean zero and precision s. When making a forecast each analyst weights his or her common and idiosyncratic information by its respective precision (h and s). The intuition of the model arises from the recognition that these fundamental characteristics of analysts' information (h and s) will be reflected differently in the observable characteristics of their forecasts -- specifically, the squared error in the mean forecast (SE) and forecast dispersion (D). BKLS essentially characterize *expected SE* and D in terms of h and s. They then reverse these relationships and express the precision of individual analysts' common (h) and idiosyncratic (s) information in terms of the *expected* squared error in the mean forecast (SE), *expected* forecast dispersion (D) and the number of analysts forecasting (N) as follows (from BKLS Corollary 1; 428):

Common Information Precision: $$h = \frac{SE - \frac{D}{N}}{[(1-\frac{1}{N})D + SE]^2}, \quad (1)$$

and *Idiosyncratic Information Precision*: $$s = \frac{D}{[(1-\frac{1}{N})D + SE]^2}. \quad (2)$$

These measures of information precision are related to two fundamental properties of analysts' information, namely, the level of informedness (k) and the level of consensus (ρ) as follows:

Informedness: $$k \equiv h + s, \quad (3)$$

and *Consensus*: $$\rho = \frac{h}{h+s}. \quad (4)$$

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[3] Additional BKLS assumptions are: (2) there are no differences in expected forecast accuracy across analysts; (3) forecast errors are normally distributed; and (4) all information is either common to all analysts, or idiosyncratic to a particular analyst. The extent and degree to which any of these assumptions are violated could impinge upon this study. Barron et al. (2002b) conduct an examination of the extent to which violations of any of these assumptions affect the operationalization of the BKLS framework. They conclude that the underlying assumptions of BKLS are a reasonable first approximation and that violations of the underlying assumptions of the framework are not large enough in magnitude to challenge the empirical validity of the framework. Nevertheless, I replicate the validity tests of Barron et al. (2002b). See section 5.4.

Where informativeness (k) is the precision of an individual analyst's total information (common and idiosyncratic). Consensus is, in essence, the across-analysts correlation in forecast errors. While it is a more general measure than the information precision measures (h, s and k), in that it does not require as many restrictive assumptions (see Barron et al. 2002b), it is most easily understood as the ratio of the precision of common information to the precision to the total information available to an individual analyst. These constructs, informedness (k) and consensus (ρ) are the same constructs examined by Holthausen and Verrecchia (1980), Indjejikian (1991) and Fischer and Verrecchia (1998). Thus, the BKLS consensus construct can be used to test the model of Indjejikian (1991) using a direct measure of the theoretical construct he examines, rather then using an indirect proxy variable.

3. Literature Review and Hypotheses Development

In this study I take the BKLS approach to measuring pre-announcement and earnings announcement period information. This approach allows the separate testing of the relation between firm size and individual analysts' common and idiosyncratic (or uniquely private) information acquisition. My hypotheses are based upon the model of Indjejikian (1991) and prior empirical evidence documenting greater levels of pre-announcement information for larger firm (e.g., see Atiase 1985). Atiase (1985) reports that public pre-disclosure information is increasing in firm size. He predicts that the level of public information is increasing in firm size, as larger firms, because of their greater social importance, attract more feature articles in publications such as *Businessweek* and the *Wall Street Journal*. Atiase's (1985) arguments suggest that, prior to an earnings announcement, the level of pre-disclosure information is higher for larger firms.

Indjejikian (1991) models the optimal disclosure decision of managers as they affect investors' informedness and consensus regarding future cash flows. In adopting the predictions of Indjejikian, I assume a relationship between informedness (k) and consensus (ρ) regarding future earnings and informedness and consensus regarding future stock returns. Consistent with this belief, evidence indicates that a significant proportion of investors have short-term trading horizons of less than one year. For example, during 1999 the average holding period for stocks was just over eight months (see Morgenson 2000).[4] Informedness (k) and consensus (ρ) regarding near-term earnings is likely to be a key focus of short-term investors. As the most recent edition of *Graham and Dodd's Security Analysis* comments:

> A considerable part of the activity of Wall Street analysts -- as reflected in the advisory publications of financial services and in brokerage-house reports -- is devoted to the effort to forecast near-term changes in earnings. Furthermore, many of their conclusions as to the dearness or cheapness of individual shares (other than growth stocks) appear to be based on a capitalization of the profits and dividends expected in the next 12 months or so. This is a recognition of the fact that announcements of the latest earnings do influence stock prices -- at least in the short run (Cotter et al. 1988; 552).[5]

Disagreement about near-term earnings prospects also is a cause of significant trading activity by individuals in the investment community (e.g., see Bamber et al. 1997). Given their short-term trading horizons, many investors focus upon short-term stock returns generated by near-term earnings announcements. Combined with the large number of analysts responding to these investors' demand for information (see Stickel 1989), this suggests that there is a close relation between analysts' informedness (k) and consensus (ρ) regarding near-term earnings and the informedness and consensus among many investors regarding their (short horizon) stock returns.

According to Indjejikian's (1991) disclosure model, higher levels of public pre-disclosure informedness (or $1/V$ in his model) suggests a higher optimal level of announcement-related disclosure (that is to say, a more informative earnings announcement). However, increases in disclosure can lead to decreases in investor utility if the increased disclosure is commonly interpreted. The decrease in utility to an individual investor arising from increased ex-ante price risk, because if an increase in disclosure is commonly interpreted by all market participants, this will lead to large price changes. In particular, a combination of high Informedness (high precision of information) and high consensus (little or no information heterogeneity among market participants) will lead to higher ex-ante price risk. The decrease in investor utility from

[4] See also "Wake-up call" *The Economist* (March 25, 2000; 79-80) which reports that, on average, every share of every company listed on the New York Stock Exchange is traded an average of at least once a year.

[5] Confirming the focus of analysts upon short term forecasting horizons, the 1999 edition of the I/B/E/S Detail file, for example, contains 551,166 forecasts made during 1997. Of these forecast, 365,198 (66.3 percent) had a horizon of less than one year.

higher ex-ante price risk can overwhelm the increase in utility the investor derives from sharing in the information herself.

Indjejikian (1991) assumes that maximizing investor welfare is the objective when firms choose their optimal level of public disclosure. He then examines the impact of costly information interpretation on the optimal level of private interpretations resulting from increased public disclosure (the increased disclosure that occurs at an earnings announcement). In other words, he examines the degree to which investors are willing to incur costs to generate heterogeneous inferences and decrease consensus (ρ). Such heterogeneous interpretations could be supplied to investors by active analysts (see Barron et al. 2002b). These costs are compared to benefits represented by the term:

$$\left(2-\rho\right)+\frac{T}{k1}, \text{ (Indjejikian 1991; 289),}^{6} \qquad (5)$$

where T is the amount of noise in the market for the underlying security.

Equation (5) suggests that the benefits to investors from lowering consensus increase with informedness, *k1*. Barron et al. (2002b) demonstrate empirically that decreases in consensus result from earnings announcements. Thus, I examine two specific predictions that arise from the following proposition from Indjejikian:

> PROPOSITION 3. The optimal level of informedness from an earnings announcement, denoted Δk, increases with the pre-announcement level of informedness, denoted *k1* (paraphrased from Indjejikian 1991; 292).

That is, Indjejikian, points to potentially greater benefits from increases in informativeness associated with disclosures for firms with higher levels of pre-announcement informativeness (*k1*). Together with Atiase's (1980) argument that *k1*, the pre-announcement level of informedness, is greater for larger firms, this suggests that the benefits of increases in informedness associated with public disclosures are potentially greater for large firms than small

[6] To simplify this expression investors' constant absolute risk tolerance, which Indjejikian (1991) denotes as r, is set to one.

firms.[7] In summary, it is expected that the costs of disclosure are decreasing in firm size, while the benefits of disclosure are increasing in firm size. This leads to my first hypothesis:

> H1: The increase in informedness from an earnings announcement, denoted Δk, is greater for large firms than small firms.

As can be seen in equation (5) above, proposition 3 of Indjejikian (1991) results because investors derive more of a benefit from costly decreases in consensus regarding a firm's disclosures relative to the benefit they derive from increases in the informedness resulting from these disclosures. This leads to the second hypothesis regarding larger firms:

> H2: The reduction in consensus from an earnings announcement is greater for larger firms than smaller firms.

Tests of these two hypotheses are important for increasing financial accountants' understanding of the informational differences between larger and smaller firms. Prior evidence, however, does not speak directly to how the amount of new information accounting releases trigger differs across larger and smaller firms. The relation between the amount of new information the earnings announcement conveys to market participants (the change in informativeness -- denoted Δk) and the total amount of pre-announcement information (denoted $k1$) determines price reactions to public announcements. More specifically, in a model of rational trade, Kim and Verrecchia (1991; Proposition 1; 311) show that the price reaction to an earnings announcement is proportional to the precision of the new information resulting from the announcecment (Δk) relative to the total amount (precision) of post-announcement information ($k1+\Delta k$). More formally, market reactions to earnings announcements are predicted to increase with the term $\Delta k/(k1+\Delta k)$. In essence, the whole term $\Delta k/(k1+\Delta k)$ is inversely related to firm size. In this study, I directly measure both $k1$ and Δk for analysts' information about future earnings, construct the ratio $\Delta k/(k1+\Delta k)$, and the expectation that this ratio decreases with firm size.

The inverse relationship between firm size and $\Delta k/(k1+\Delta k)$ that I expect could exist for several reasons. For example, it could exist if both pre-announcement information, $k1$, and

[7] Furthermore, as economies of scale exist in disclosure (e.g., see Lang and Lundholm 1996), this suggests that the costs of disclosure are also decreasing in firm size.

announcement-period information, Δk, are positively correlated with firm size, but *k1* is correlated more strongly with size than Δk. This condition is expected if larger firms have a greater incentive to increase the informedness of their public disclosures, and elite market participants with superior information processing skills (e.g., analysts) have a greater incentive to use these releases to generate new idiosyncratic (or uniquely private) information. It follows that this expectation points to the importance of directly measuring *both* $k1$ and Δk for analysts' information about future earnings, constructing the ratio $\Delta k / (k1 + \Delta k)$, and directly testing the expectation that this ratio is decreasing in firm size.

Based on the theoretical arguments of Indjejikian (1991), and prior evidence indicating a greater analyst following for larger firms (see Bhushan 1989b; O'Brien and Bhushan 1990), I also expect that these incentives are greater for larger firms than smaller firms. Further, investors' potential trading profits are greater for larger firms because of greater liquidity, which is expected to increase the incentives for market participants to acquire idiosyncratic information (see Atiase 1980). Thus, the BKLS model is used to directly test this argument regarding firm size, as it relates to analysts' announcement-period information (Δk).

I also compare the nature of larger and smaller firms' pre-disclosure information. Atiase (1980) predicts that both public and private pre-disclosure information are increasing in firm size. He hypothesizes that the level of public pre-disclosure information is increasing in firm size as larger firms, because of their greater social importance, will attract more feature articles in publications such as *Businessweek* and the *Wall Street Journal*. Because of their more prominent role in the economy, larger firms will attract greater media attention, which, in turn, will lead to a greater amount of public information being disseminated for these firms. Atiase (1980) also predicts that the level of pre-announcement private information will be increasing with firm size as larger firms attract greater private information acquisition activity among investors, because of the greater potential trading profits, due to the greater liquidity and lower transaction processing costs for larger firms (see Atiase 1980; King et al. 1990, respectively). While the extant empirical literature on the relation between firm size and pre-disclosure information proposes that both public and private pre-disclosure information are increasing in firm size. I separately test these predictions as it relates to individual analysts' common and idiosyncratic information.

4. Study Design and Data Selection

4.1 Study Design

I select forecasts of annual earnings made during eight forecast windows. These forecast windows are selected to be directly before and after four prior earnings announcements. The earnings announcements used are: the prior-year annual earnings announcement, and the announcement of first, second and third quarter earnings for the current year. I use the 45-day period prior to the Compustat announcement dates as the pre-announcement forecast window (days –45 through –1, where day 0 is the Compustat earnings announcement date) and the 30-day period immediately after the announcement dates as the post-announcement forecast window (days 0 through +29, inclusive). The 30-day forecast window immediately after the earnings announcement dates tends to ensure that the forecast revisions made during this period capture primarily the information effects of the accounting data announced (see Stickel 1989).[8,9]

In applying the BKLS model, I substitute ex-post realized dispersion and squared error in the mean forecast as proxies for *expected* dispersion (*D*) and squared error (*SE*). This substitution of ex-post realizations for expected values introduces measurement error into my measures of expected dispersion and squared error and into our empirical measures of the information variables of the BKLS framework -- $\hat{h}$, $\hat{s}$, $\hat{k}$ and $\hat{\rho}$.[10]

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[8] Similar to Bamber et al. (1997), I use a longer pre-announcement forecast window because analysts are less likely to update their forecasts of annual earnings immediately prior to earnings announcements (see Stickel 1989).

[9] This 30-day post-announcement forecast window may encompas the public release of a firm's 10K or 10Q reports (see Easton and Zmijewski 1993). Given that I test size-based hypotheses regarding changes in analysts' information following earnings announcements, the results could be confounded by differenced across large and small firms in the timing of the release of 10K and 10Q reports. Easton and Zmijewski (1993), however, find no significant difference in the time lag between earnings announcement dates and 10K/10Q filing dates for large and small firms.

[10] In addition, the use of forecast windows to collect individual forecasts introduces the possibility that stale forecasts (which are more likely to be made early in the forecast window) will introduce noise into my estimators. Barron et al. (2002), however, report similar results using 45 and 30-day forecast windows and shorter forecast windows.

Forecasts from the pre- and post-announcement forecast windows are matched across individual analysts to ensure that when comparing analysts' information before and after earnings announcements, I base my analysis on a constant set of individual analysts.[11] Also, analysts revising their forecasts soon after accounting releases are more likely to be using their own assessment of the financial data announced. It follows that these analysts are less liable to be relying upon the forecasts of other analysts (Trueman 1994; Barron and Stuerke 1998).

Using these observed forecasts, ex-post realized (squared) error in the mean forecast (denoted $\hat{SE}$) and dispersion (denoted $\hat{D}$) are calculated as follows:

$$\hat{SE}_{jtw} = \left(A_{jt} - \overline{F}_{jtw}\right)^2, \tag{6}$$

and

$$\hat{D}_{jtw} = \frac{1}{N_{jtw} - 1} \sum_{i=1}^{N} \left(F_{ijtw} - \overline{F}_{jtw}\right)^2, \tag{7}$$

where $\hat{SE}_{jtw}$ is the observed squared error in the mean forecast for firm j in year t for forecast window w; $\hat{D}_{jtw}$ is the observed dispersion among the forecasts for firm j in year t, made during forecast window w; A_{jt} is the actual earnings for firm j in year t; F_{ijtw} is the forecast from analyst i, for firm j in year t, made during forecast window w; $\overline{F}_{jtw}$ is the mean of the forecasts for firm j in year t, made during forecast window w; and N_{jtw} is the observed number of forecasts for firm j in year t, made during forecast window w. These estimates of the squared error in the mean forecast ($\hat{SE}$) and dispersion ($\hat{D}$) are scaled by the absolute value of actual EPS. Scaled $\hat{SE}$ and $\hat{D}$, together with the observed number of analysts forecasting (N), are substituted into equations (1) through (4) to calculate the information variables of interest from the BKLS framework ($\hat{h}$, $\hat{s}$, $\hat{k}$ and $\hat{\rho}$).[12]

4.2 Sample Selection

[11] This matching also ensures that the number of analysts forecasting for each firm-year is constant across the forecast windows before and after earnings announcements. Hence, my measure of forecast dispersion (D) (sample variance) and the derived BKLS measures (h, s, k and ρ) are undistorted by changes in the number of forecasts used (N). Changes in h, s, k and ρ are, thus, unaffected by changes in the number of forecasts used.

[12] Observations with absolute values of actual EPS less than 10 cents are removed from the sample as a control for extreme observations induced by the choice of scaling variable. This step results in approximately 3.25 percent of the observations being dropped for each of the prior earnings announcements. I scale by actual EPS to ensure that $\hat{SE}$ and $\hat{D}$ are comparable across firm-years. Using unscaled $\hat{SE}$ and $\hat{D}$, scaling by the squared value of actual earnings, and scaling by stock price, however, all produce very similar results to those reported here.

The primary samples of firm-years for the eight forecast windows contain observations from 1986 to 1997, inclusive, that meet the following four requirements:

1) quarterly earnings announcement dates for *either* first, second or third quarterly earnings for the current year, or forth quarter for the prior-year, are available from either the Active or Research Compustat quarterly files;
2) annual EPS data for the current year is available from the I/B/E/S Actual earnings announcements file;
3) at least two new forecasts of annual earnings for the current year are available on the I/B/E/S Detail file from individual analysts in *both* the 45-day forecast window before and the 30-day forecast window after the Compustat earnings announcement dates for prior earnings realizations; and[13,14]
4) market capitalization data, measured at firms' fiscal year end, is available from either the Active or Research Compustat annual files. This data is deflated to constant 1985 CPI-dollars.

Forecast windows before earnings announcements are subscripted B, and those after earnings announcements are subscripted A. The prior year annual earnings announcements are denoted PA, while first, second and third quarterly earnings announcements for the current year are denoted Q1, Q2 and Q3, respectively. The sequence of the eight forecast windows is thus denoted: PA_B, PA_A, $Q1_B$, $Q1_A$, $Q2_B$, $Q2_A$, $Q3_B$ and $Q3_A$. These sample selection procedures produce a sample of 2,786 firm-years for the prior annual earnings announcement (forecast windows PA_B and PA_A) and samples of 3,734, 3,530 and 4,365 firm-years, respectively, for the first, second and third quarterly earnings announcements for the current year -- see Panel A of Table 1. Also, as can be seen in Panel A of Table 1, while there are significant numbers of observations in each year of the sample period, there does tend to be more observations in the later years of the sample period, 1986 through 1997 inclusive. These samples contain multiple

[13] In rare cases where multiple forecasts are available from individual analysts within individual forecast windows, only the last forecast before the earnings announcement or the first after the earnings announcement date is selected.

[14] My sample selection procedures affect the selected samples in that for some firms analysts do not submit the revised forecasts required for inclusion in my samples. This non-reporting weights the samples of firm-years more heavily toward larger firms. Given that I test size-based hypotheses, the sample selection procedures, thus, reduce the power of the tests. In addition, while matching on a larger number of analysts is conceptually more attractive as an application of the BKLS model (see Barron et al. 2002b), this practice also weights samples of firm-years more heavily towards larger firms. Matching three (or five) analysts, however, produces similar but statistically weaker results than those reported here.

firm-year observations for each firm. My inferences, however, are unchanged when I run all my tests using one firm-year observation for each firm.[15]

(Insert Table 1 About Here)

5. Empirical Results

5.1 Firm Size and the Levels of $\hat{h}, \hat{s}, \hat{k}$ and $\hat{\rho}$

A can be seen in Panel B of Table 1, consistent with concurrent research (Barron et al. 2002b) the cross-sectional distributions of $\hat{h}, \hat{s}$, $\hat{k}$ and $\hat{\rho}$ are highly skewed.[16] Hence I use, sample medians to characterize the average levels of $\hat{h}, \hat{s}$, $\hat{k}$ and $\hat{\rho}$. To avoid drawing erroneous inferences from data dominated by extreme values, I use non-parametric statistical tests, specifically, the median scores test, which assesses the null hypotheses that an equal proportion of larger and smaller companies are above (and below) the sample median (the median of the pooled sample of large and small firms). I use the median scores test in preference to a Wilcoxon rank sum statistic, as this simpler binomial test tends to be less sensitive to the effect of measurement error (Conover 1980), which is likely to have a significant effect on my data (see section 4.1 discussion).[17]

(Table 2 About Here)

My initial tests focus upon the relationship between firm size and the levels of the information variables of the BKLS model: h, s, k and ρ. Consistent with the predictions of Atiase (1985), analysts exhibit significantly higher levels of common information ($\hat{h}$), idiosyncratic information ($\hat{s}$) and informedness ($\hat{k}$) for larger firms for all eight forecast windows used. The median scores test indicates that the levels of $\hat{h}$, $\hat{s}$ and $\hat{k}$ are significantly

[15] For example, of the 998 different firms represented in the sample of 2,786 firm-years for the prior year annual earnings announcement, 471 firms have just one observation. My inferences are unchanged when I run my analysis on just this sample of 471 firm-years. .

[16] The cross-sectional distributions of $\hat{h}, \hat{s}, \hat{k}$ are positively skewed, and $\hat{\rho}$ is negatively skewed. This is not surprising as none of these variables has a negative theoretical expectation, and are estimators based upon variance ($\hat{D}$) and squared error ($\hat{SE}$). For all eight cross-sectional distributions of $\hat{h}, \hat{s}, \hat{k}$ and $\hat{\rho}$, the Kolmogorov statistic rejects normality at the $p < 0.01$ level.

[17] My inferences are, however, unchanged when I use a Wicoxon rank sum statistics.

higher for larger firms. For all eight forecast windows the result is significant at the $p<0.01$ level (1-tailed median scores p-value) for $\hat{h}$, $\hat{s}$ and $\hat{k}$. However, as one can see in Table 1, Panel B, larger firms have a significantly *lower* level of consensus during the entire pre-announcement period studied. For all eight forecast windows studied the result is significant at the $p<0.01$ level (1-tailed median scores p-value).

5.2 Firm Size and Changes in Analysts' Information Around Earnings Announcements

I also test the relation between firm size and changes in analysts' information following earnings announcements. Initially I test the relationship between firm size (market capitalization) and the ratio $\Delta k/(k1+\Delta k)$. I calculate the ratio $\Delta k/(k1+\Delta k)$ for each firm-year in my four earnings announcement samples. That is, I calculate the levels of informedness before ($\hat{k}1$) and after ($\hat{k}2$) earnings announcements, and I calculate the change in informativeness ($\Delta\hat{k}$) as: $\Delta\hat{k}=\hat{k}2-\hat{k}1$. This data is then used to calculate the ratio $\Delta\hat{k}/(\hat{k}1+\Delta\hat{k})$. Because of the measurement error in firm-level data for average informedness ($\hat{k}\,1$ and $\hat{k}\,2$), as discussed in section 4.1, the resulting firm-level data for the ratio $\Delta\hat{k}/(\hat{k}1+\Delta\hat{k})$ is likely to be quite noisy. Nevertheless, consistent with prior market-based research results (see Atiase 1980; 1985), the median scores tests for all four earnings announcements indicate that the ratio $\Delta\hat{k}/(\hat{k}1+\Delta\hat{k})$ decreases with firm size. As Panel A in Table 3 shows, the result is significant at the $p<0.05$ level for two of the four prior accounting releases examined (1-tailed median scores p-value).

(Table 3 About Here)

While theoretical models predict that public announcements can trigger the release of both new common and idiosyncratic information (see Kim and Verrecchia 1994; 1997) prior empirical studies, which focus upon changes in market variables such as stock prices and returns surrounding earnings announcements, have not separately tested the relationship between firm size and both the new common and idiosyncratic (or uniquely private) information triggered by earnings announcements. The BKLS model, however, allows a separate testing of the relationship between firm size and *both* the new common and idiosyncratic information triggered by earnings announcements. Thus, I also test for differences across larger and smaller firms in the *changes in the precision of analysts' common ($\Delta\hat{h} = \hat{h}2 - \hat{h}1$) and idiosyncratic ($\Delta\hat{s} = \hat{s}2 - \hat{s}1$) information following financial report releases*. Consistent with my expectations based upon the findings of Barron et al. (2002), larger firms exhibit greater increases in the average precision of individual analysts' common ($\Delta\hat{h}$) and idiosyncratic ($\Delta\hat{s}$) information as a result of prior accounting releases (this result appears in Panel B of Table 2).[18] For two of the four earnings announcements selected, larger firms exhibit statistically larger increases in the precision of analysts' common information ($p<0.01$, one-tailed median scores test), while for three of the four earnings announcements larger firms have statistically larger increases in the precision of individual analysts' idiosyncratic information ($p<0.01$). It follows that larger firms have larger increases in analysts' informedness (Δk) following earnings announcements (this result appears in Panel C of Table 2). For all four accounting releases, larger firms exhibit statistically significant larger increases in analysts' average level of informedness following accounting releases ($p<0.01$). Similarly, Panel C of Table 2 shows that for three of the four earnings announcements studied, larger firms have statistically significant larger *decreases* in consensus ($p<0.05$).

(Figure 1 About Here)

These results support Schipper's (1991) argument that, in part, analysts serve as sophisticated processors of financial reports. My findings indicate that analysts fulfill this function where the demand for such information is highest, that is for larger firms. Figure 1 summarizes these results showing that the increases in informedness (Δk) and decreases in consensus ($\Delta\rho$) surrounding earnings announcements are more pronounced for larger firms then for smaller firms. Note also that these increases in informedness and decreases in consensus concentrate around earnings announcements (see also Barron et al. 2002b).

[18] While conference calls are more common for larger firms (Tasker 1998), my results do not appear to be driven by conference calls. Splitting my sample period in two (1986 through 1992; and 1993 through 1997) produces qualitatively identical size results for both sub-periods.

In sum, my evidence is consistent with prior findings that more pre-disclosure information exists for large firms than for small firms (e.g., see Atiase 1985). However, using an analyst forecast-based approach, I add to this literature by documenting that the precision of *both* common (mainly public) and idiosyncratic (or uniquely private) pre-disclosure information increase in firm size. My results confirm the relationship between firm size and stock price changes associated with earnings announcements, however, they also indicates that the relationship between firm size and a firm's information environment (demand for information) is somewhat more complex. Firm size also appears to be positively associated with the changes in analysts' commonly inferred information triggered by accounting releases ($\Delta\hat{h}$), a finding consistent with the observation that large firms produce more precise financial disclosures than small firms. Intuitively, one could think of this proclivity as deriving from the fact that larger firms are likely to have more extensive disclosures in their financial report releases -- that they tend to disclose information on more business segments, for example. The accounting releases of larger firms also appear, however, to be associated with larger increases in analysts' private information ($\Delta\hat{s}$), as well as larger decreases in analyst consensus.

This result implies that the financial report releases of larger firms contain a greater number of commonly observable financial signals, which in turn trigger a greater number of new idiosyncratic (uniquely private) information signals for analysts (see Kim and Verrecchia 1994; 1997; Barron et al. 2002b). Also, given the size-based incentives for private information acquisition (Atiase 1985), analysts seem likely to invest greater effort developing private knowledge regarding the errors in the financial reporting systems of larger firms. This additional knowledge for larger firms allows analysts to generate a greater amount of new uniquely private (idiosyncratic) information concurrent with financial report releases for these firms (see Kim and Verrecchia 1994, 1997; and Barron et al. 2002b).

Larger decreases in consensus result from the fact that the precision of idiosyncratic information increases faster than the precision of common information for larger firms. This is particularly significant given the fact that larger firms start with a lower level of consensus. In other words, firm size is a significant determinant of idiosyncratic information acquisition (or triggering) during announcement periods. This finding is consistent with the idea that elite market participants (actively updating analysts in this case) with superior information processing skills have the greatest incentives to use accounting releases to generate new privately inferred information about large firms.

5.3 Firm Size and the Informational Benefits of Aggregating Individual Forecasts

At low levels of consensus ($\hat{\rho}$), *relatively* more idiosyncratic information is impounded in the mean forecast. That is to say, the benefits of forecast aggregation (e.g., see Brown 1991), or the likelihood that the mean forecast is more accurate than an individual forecast, are related to the number of analysts forecasting and the level of consensus. It follows that when consensus is low, the mean forecast is likelier to be more accurate -- that is, have a smaller absolute error -- than individual forecasts (see Holthausen and Verrecchia 1990; BKLS; Barron et al. 2002b). An implication of this result is that the greater heterogeneity (lower consensus) among the active analysts forecasting for larger firms means that there is more informational benefit from aggregating individual forecasts for larger firms.

Given my prior results, documenting an inverse relationship between BKLS consensus and firm size, I expect that, controlling for the number of analysts forecasting, there will be a positive relationship between firm size and the relative frequency with which the mean forecast is more accurate than an individual forecast. I use a probit model to test this expectation. For each firm-year within each of the eight forecast windows I study, I compare the accuracy (the absolute error) of the mean forecast with that of the most recent (last) individual forecast.[19] Prior research, however, indicates that forecast recency is an important determinant of forecast accuracy (e.g., see Brown 1991). As a result, I control for difference in the age of the most recent forecast and the average age of the forecasts comprising the mean forecast (*DAGE*). In addition, larger firms are associated with a greater number of analysts processing earnings news

[19] The results using percentage forecast errors (scaling by the absolute value of actual EPS) are identical.

into forecasts (e.g., see Bhushan 1989b; O'Brien and Bhushan 1990; Lys and Soo 1995). I also include the number of analysts forecasting (*N*) as a control variable.

To test the association between firm size and the relative frequency with which the mean forecast is more accurate, I pool all available firm-years for all eight forecast windows and include indicator variables for each year and forecast window. The following fixed effects probit model is then employed:

$$Prob\left(E^{M}_{jtw} < E^{I}_{jtw}\right) = \alpha_0 + \alpha_1 DAGE_{jtw} + \alpha_2 \ln MV_{jtw} + \sum_{w=2}^{W} \lambda_w WD_w + \sum_{t=2}^{T} \delta_t YD_t + \varepsilon_{jtw} \qquad (8)$$

where: E^{M}_{jtw} is the absolute error in the mean forecast for firm *j* in year *t*, during forecast window *w*; and E^{I}_{jtw} is the absolute error in the most recent individual forecast for firm *j* in year *t*, during forecast window *w*. A dummy variable is created coded one when $E^{M}_{jtw} < E^{I}_{jtw}$, and zero otherwise;

$lnMV_{jtw}$ and is the natural log of the market value of firm *j* in year *t* for forecast window *w*;

YD_{jtw} is a dummy variable equal to one for year *t*, and zero otherwise; and

WD_{itw} is a dummy variable equal to one for forecast window *w*, and equal to zero otherwise.

This results in a sample of 15,115 firm-years pooled across all eight forecast windows and all twelve sample years. In a test of equation (8) using this sample, α_2 is found to be positive and significant (p<0.01, two-tailed chi-squared p-value) -- see results for Model 1 in Table 4. That is, there is a positive association between firm size and the relative frequency with which the mean forecast is superior (more accurate) than the most recent individual forecast.[20] To further confirm this association between the benefits of aggregating increasingly heterogeneous forecasts and firm size, I also estimate a probit models similar to equation (8) above, but substituting $\hat{\rho}$ for firms size (natural log of market capitalization) and, including both size and $\hat{\rho}$ as independent variables. As can be see in Table 4, the results from the estimation of these alternative models (numbered 2 through 5 in Table 4) show that high market capitalization and low consensus are both associated with increased benefits from aggregating individual forecasts.

[20] As a guard against the possible effects of within-firm dependence upon this test, an OLS regression is also used to evaluate equation (8) where firm-year observations for all eight forecast windows are replaced by the average (mean) values for all variables across all firm-years available for each firm. The results are consistent with those from the probit model reported above.

However, when both independent variables are included in the model, only consensus is significant, confirming that the relationship between firm size and the benefits of aggregating individual forecasts is derived from an association between firm size and the heterogeneity of individual forecasts.

(Insert Table 4 About Here)

Another way of looking at this evidence regarding absolute forecast errors is to consider the expression BKLS analytically derive for the squared error in the mean forecast (see BKLS equation 14; 426):

$$SE = \frac{1}{k}\left(\rho + \frac{1-\rho}{N}\right). \tag{9}$$

Where N is the number of analysts forecasting, k is the average level of informedness of analysts and ρ is the level of consensus among these analysts. The squared error in the mean forecast (*SE*) is, thus, increasing in ρ, but decreasing in k and N. I document a positive relationship between firm size and both k and N, and a negative relationship between firm size and ρ. The observed smaller earnings surprises for larger firms, that is to say the smaller errors in the mean forecasts of larger firms are, thus, due to three effects. One, a greater number of analysts forecasting for larger firms, two, a higher level of informedness and, three, a lower level of consensus among these analysts.

These results also extend prior research modeling financial analyst forecast superiority (relative to time series models) as a function of attributes of the firm's information environment (see Brown et al. 1987; Kross et al. 1990). That is, the results of this study indicate that there is also a link between the superiority of the mean forecast relative to individual analyst forecasts and attributes of the firm's information environment, specifically firm size.

5.4 Robustness

Researchers have considered the possibility that analysts systematically issue biased forecasts and recommendations (e.g., see Lim 2001; Michaely and Womack 1999). The BKLS framework used here, however, assumes unbiased forecasts (Barron et al. 2002b). As such, the presence of large systematic biases in my forecast data may affect my results. While some recent studies show that the apparent optimistic bias in analysts forecasts has diminished in recent year (e.g., see Brown 2000), that is during the sample period use in this study, I nevertheless examine the extent to which my results are affected by systematic optimism among the forecasts I use.

As a test of the sensitivity of my results to the presence of bias in my sample, I calculated the average optimism for the individual forecasts in each of my eight forecast windows. Consistent with prior evidence (Richardson et al. 2001), I find the average "optimism" to be lower for later forecast windows.[21] I then re-calculated myr empirical proxy for the squared error in the mean forecast (SE) as follows:

$$\hat{\mathrm{SE}}^{*}_{\mathrm{jtw}} = \left(\left(A_{jt} - \overline{F}_{jtw}\right) - \frac{1}{T}\frac{1}{J}\sum_{t=1}^{T}\sum_{j=1}^{J}\left(A_{jt} - \overline{F}_{jtw}\right) \right)^{2}, \tag{10}$$

where $\hat{SE}^{*}_{jtw}$ is the observed squared error in the mean forecast for firm *j* in year *t* and forecast window *w,* adjusted for the average level of "optimism" for all forecasts for that forecast window; A_{jt} is the actual earnings for firm *j* in year *t*; F_{ijtw} is the forecast from analyst *i*, for firm *j* in year *t*, made during forecast window *w*; and $\overline{F}_{jtw}$ is the mean forecast of firm *j* in year *t*, made during forecast window *w*. Thus, I adjusted the squared error in the mean forecast for the average level of "optimism" in all the forecasts for that window. Repeating my previous analysis, I substitute the average-optimism adjusted estimate of the squared error in the mean forecast, $\hat{\mathrm{SE}}^{*}_{\mathrm{jtw}}$ from equation (10) above, and the estimate of the level of dispersion among forecasts ($\hat{D}_{jtw}$), from equation (7), together with the observed number of analysts forecasting (*N*) into the BKLS framework, that is equations (1) through (4), to calculate estimates of the information variables of interest ($\hat{h}$, $\hat{s}$, $\hat{k}$ and $\hat{\rho}$). My inferences are unchanged using this alternative average-bias corrected estimator.[22]

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[21] The mean (and median) percentage error for all individual forecasts in my sample range from 9.4 (2.4) in the PA_B forecast window to 2.5 (0.0) in the $Q3_A$ forecast window.

[22] I also test the possibility that the results of my hypotheses tests could be affected by dependencies that result from correlated forecast errors within each of our sample years (see Keane and Runkle 1998). As a diagnostic measure, I re-calculate the squared error in the mean forecast as follows:

Recent research points to the possibility that managers engage in "forecast management," that is managing the expectations of analysts (e.g., see Matsumoto 2002), and/or that observed forecast errors are determined by earnings management to "meet or beat" analysts' expectations (see Burgstahler and Eames 2001; and Beatty et al. 2002). My analysis is consistent with the notion that managers avoid earnings surprises by managing the expectations of analysts via more pre-announcement disclosure to analysts. However, the same cannot be said about earnings management to "meet or beat" analyst's expectations. This results from the fact that if managers adopt analysts' expectations as a performance benchmark, the resulting actual earnings realization is conditional upon analysts' forecasts.

As a result, I conduct a supplemental analysis excluding observations where such earnings management to "meet or beat" analysts' expectations is most likely to be present. Specifically, I replicate my tests excluding firm-years with small positive earnings surprises (positive earnings surprises between 0 and 5 cents), as these are the observations most likely affected by the presence of earnings management. My results are unaffected by this adjustment.[23]

6. Concluding Remarks

Using a sample of forecasts from actively updating analysts who revise their forecasts around prior earnings announcements, I provides *direct* evidence regarding the relationship between the precision of market participants'-- specifically, analysts -- pre-announcement

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$$\hat{SE}^{**}_{jtw} = \left(\left(A_{jt} - \overline{F}_{jtw} \right) - \frac{1}{J} \sum_{j=1}^{J} \left(A_{jt} - \overline{F}_{jtw} \right) \right)^2 , \tag{11}$$

where $\hat{SE}^{**}_{jtw}$ is the squared error in the mean forecast for firm *j* in year *t* for forecast window *w*, adjusted for the average level of error across all analysts for forecast window *w* in year *t*. Thus, for each forecast window we adjust the squared errors for the average level of $\hat{SE}$ for that year. Again, I substitute the new estimate of squared error in the mean forecast ($\hat{SE}^{**}_{jtw}$), from equation (11) above, and the estimate of the level of dispersion among forecasts ($\hat{D}_{jtw}$), from equation (7), together with the observed number of analysts forecasting (*N*), into the BKLS framework, that is equations (1) through (4). Replicating all my hypotheses tests, I find that my inferences are unaffected by this adjustment.

[23] In addition, prior studies report a "structural shift" consistent with a greater frequency of analyst's expectations being managed after 1992 (see Matsumoto 2002). However, splitting my sample period in two sub-periods (1986 through 1992; and 1993 through 1997) I find that my inferences continue to hold for both subperiods..

information and firm size. My results confirm prior evidence from market-based studies (see Atiase 1985). That is, I confirm that the precision of pre-announcement information increases with firm size. I add to this literature by documenting that the precision of *both* analysts' common (mainly public) and idiosyncratic (uniquely private) pre-disclosure information of analysts increases with firm size. I also find that the precision of both new common and idiosyncratic information triggered by financial report releases is higher for larger firms.

My results also extend the prior analyst following literature. Prior studies of analyst following and forecast errors indicate that larger firms tend to have a greater analyst following (Bhushan 1989b; O'Brien and Bhushan 1990) and smaller forecast errors (Lys and Soo 1995). This study documents additional differences in the properties of analysts' information for larger firms. In particular, I document that the precision of both common and idiosyncratic (uniquely private) information increase with firm size. This, however, is particularly the case for analysts' idiosyncratic information.

I also documents that the decrease in the consensus (commonality of information) among analysts following earnings announcement is greater for larger firms (see Barron, Byard and Kim 2002b). This finding suggests that analysts serve as sophisticated processors of financial report releases (Schipper 1991), and that analysts fulfill this function to a greater degree when the demand for such information is greatest, that is for larger firms. In fulfilling this role, the actions of analysts produce more accurate aggregate (mean) forecasts, especially for larger firms. That is to say, the benefits of aggregating individual forecasts to generate more accurate summary earnings expectation estimates are related to firm size.

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TABLE 1
Sample Selection and Descriptive Statistics

Panel A: Sample Description

	Prior Ann. Earning Ann.	Qtr 1 Earning Ann.	Qtr 2 Earning Ann.	Qtr 3 Earning Ann.
Number of firm-years with Compustat earnings announcement data and required IBES data (individual forecasts before and after announcement and IBES actual EPS)	3,259	4,242	4,027	4,997
Number of firm-years with required IBES data and also with Compustat market capitalization data	2,786	3,745	3,530	4,365

Annual Distribution of Observations -- e.g. Qtr 3[a]

Sample Years	Firms with required IBES forecast data	Firms with required IBES forecast data and Compustat market capitalization data
1986	251	167
1987	329	212
1988	358	234
1989	311	280
1990	345	311
1991	383	340
1992	393	354
1993	442	392
1994	447	403
1995	545	490
1996	540	526
1997	663	656
Total number of firm-years	4,997	4,365

Panel B: Descriptive Statistics -- e.g. $Q3_A$ Forecast Window

	Mean	Median	Std Dev
Market Capitalization (millions of 1985 CPI-deflated dollars)	3,300	928	7,663
$\hat{h}$	554.21	39.74	11,915.98
$\hat{s}$	2,511.41	42.93	23,513.33
$\hat{\rho}$	0.51	0.70	0.52

a The distributions of observations across sample years are very similar for the other three earnings announcements.

TABLE 2
Analysts' Information and Firm Size

Panel A: Level of Informedness ($\hat{k}$) and Consensus ($\hat{\rho}$) - Larger Vs. Smaller Firms

		Median Informedness ($\hat{k}$)			Median Consensus ($\hat{\rho}$)		
Forecast Windows[a]	Sample Size[b]	Large Firms	Small Firms	One-Tail P-Value[c]	Large Firms	Small Firms	One-Tail P-Value[c,d]
PA_B	2,786	22.65	10.19	<0.01	0.89	0.95	<0.01
PA_A	"	31.81	15.25	<0.01	0.87	0.94	<0.01
$Q1_B$	3,745	34.30	14.24	<0.01	0.86	0.94	<0.01
$Q1_A$	"	51.51	23.81	<0.01	0.82	0.92	<0.01
$Q2_B$	3,530	53.59	25.84	<0.01	0.82	0.92	<0.01
$Q2_A$	"	100.16	52.97	<0.01	0.73	0.89	<0.01
$Q3_B$	4,365	116.92	63.66	<0.01	0.74	0.86	<0.01
$Q3_A$	"	275.18	175.61	<0.01	0.64	0.79	<0.01

Panel B: Level of Precision of Common ($\hat{h}$) and Private ($\hat{s}$) Information - Large Vs. Small

		Median Precision of Common Information ($\hat{h}$)				Median Precision of Private Information ($\hat{s}$)		
Forecast Windows[a]	Sample Size[b]	Large Firms	Small Firms	One-Tail P-Value[c]	Value[c]	Large Firms	Small Firms	One-Tail P-
PA_B	2,786	7.34	4.28	<0.01		2.13	0.34	<0.01
PA_A	"	10.05	5.78	<0.01		3.00	0.63	<0.01
$Q1_B$	3,745	13.17	6.53	<0.01		3.66	0.66	<0.01
$Q1_A$	"	15.95	9.54	<0.01		6.69	1.43	<0.01
$Q2_B$	3,530	18.23	10.62	<0.01		6.91	1.34	<0.01
$Q2_A$	"	23.68	15.79	<0.01		17.61	4.23	<0.01
$Q3_B$	4,365	34.39	20.63	<0.01		21.42	6.42	<0.01
$Q3_A$	"	48.33	30.96	<0.01		66.23	11.70	<0.01

[a] Forecast windows are selected before (subscripted B) and after (subscripted A) earnings announcements. Forecast windows before announcements run from day –45 through –1, where day 0 is the Compustat announcement date. Forecast periods after earnings announcements run from day 0 through +29, inclusive. The earnings announcements used are: the prior annual earnings announcement (denoted PA), and the announcement of first, second and third quarterly earnings for the current year (denoted Q1, Q2, and Q3, respectively).

[b] Number of firm-yea. Forecast windows before and after earnings announcement are matched across firms and analysts. This data is matched with fiscal year-end market capitalization data from the Active and Research files of Compustat. Market capitalization data for all firm-years is deflated to constant 1985 CPI-dollars. Samples for all four earnings announcements are partitioned into large and small samples using the sample medians -- \$1,455m (prior annual); \$1,097 (Qtr 1); \$1,138 (Qtr 2); and \$928m (Qtr 3).

[c] Median score test p-value. The median score test is used to evaluate the probability that the samples of large and small firm-years come from the same populations (Conover 1980). The null hypothesis tested is that the fraction of observations for the samples of large and small firms above and below the pooled sample median (that is to say, pooled large and small samples) is the same. The alternative (one-tailed) hypothesis is that a greater fraction of the observations from the sample of large firms is above the median for the pooled (large and small firm) sample.

[d] The alternative (one-tailed) hypothesis is that a greater fraction of the observations for the sample of large firms is *below* the sample median for the pooled (large and small firm) sample.

TABLE 3
Changes in Analysts' Information Around Financial Report Releases – Larger Vs. Smaller Firms

Announcement Periods[a]	Sample Size[b]	One-Tailed Alternative Hypo. Tested[c]	Median Scores Test One-Tailed P-Value[d]	One-Tailed Alternative Hypo. Tested[c]	Median Scores Test One-Tailed P-Value[d]
Panel A: Median Change in Informedness ($\Delta\hat{k}$) Scaled by Post-Announcement Informedness ($\hat{k}1+\Delta\hat{k}$) - Larger Vs. Smaller Firms[1]					
Prior Annual	2,786	$\left(\frac{\Delta\hat{k}}{\hat{k}1+\Delta\hat{k}}\right)_{large} < \left(\frac{\Delta\hat{k}}{\hat{k}1+\Delta\hat{k}}\right)_{small}$	0.04		
Qtr 1	3,745	"	0.48		
Qtr 2	3,530	"	0.16		
Qtr 3	4,365	"	0.02		
Panel B: Median Change in the Precision of Common Information ($\Delta\hat{h}$) and Idiosyncratic Information ($\Delta\hat{s}$) – Larger Vs. Smaller Firms					
Prior Annual	2,786	$\Delta\hat{h}_{large} > \Delta\hat{h}_{small}$	0.02	$\Delta\hat{s}_{large} > \Delta\hat{s}_{small}$	0.05
Qtr 1	3,745	"	<0.01	"	<0.01
Qtr 2	3,530	"	0.06	"	<0.01
Qtr 3	4,365	"	<0.01	"	<0.01
Panel C: Median Change in Informedness ($\Delta\hat{k}$) and Consensus ($\Delta\hat{\rho}$) - Larger Vs. Smaller Firms					
Prior Annual	2,786	$\Delta\hat{k}_{large} > \Delta\hat{k}_{small}$	<0.01	$\Delta\hat{\rho}_{large} > \Delta\hat{\rho}_{small}$	0.48
Qtr 1	3,745	"	<0.01	"	0.03
Qtr 2	3,530	"	<0.01	"	0.04
Qtr 3	4,365	"	<0.01	"	<0.01

[1] $\hat{k}1$ is a measure of analysts' level of informedness prior to an earnings announcement. $\hat{k}2$ is a measure of analysts' informedness following an earnings release. The change in informedness is, thus, calculated as $\Delta\hat{k} = \hat{k}2 - \hat{k}1$. The ratio of the change in informativeness to post-announcement informativeness is then calculated as : $\frac{\Delta\hat{k}}{\hat{k}2}$ *or* $\Delta\hat{k}\Big/\left(\hat{k}1+\Delta\hat{k}\right)$.

[a] Forecast windows before announcements are 45 days in length, while forecast windows after earnings announcements are 30 days in length. See endnote a, table 1.

[b] Sample size (number of firm-years). See endnote b, table 1.

[c] In the case of the ratio of the change in informedness to the total post-announcement informedness, $\frac{\Delta\hat{k}}{\hat{k}2}$ *or* $\Delta\hat{k}\Big/\left(\hat{k}1+\Delta\hat{k}\right)$; the alternative hypotheses tested is that the ratio is smaller for larger firms. For the change in the precision of analysts' common information ($\Delta\hat{h}$), the change in analysts' idiosyncratic information ($\Delta\hat{s}$), and the change in analysts' informedness ($\Delta\hat{k}$), the one-tailed alternative hypotheses tested is that the increases in these variables are greater for large firms. Finally, for the change in the level of consensus across analysts ($\Delta\hat{\rho}$), the alternative hypotheses tested is that the *decrease* in consensus is greater for larger firms.

[d] Median scores test p-value. See endnote c, table 1.

TABLE 4
Firm Size, Analyst Consensus ($\hat{\rho}$) and the Relative Accuracy of the Mean Forecast Versus Individual Forecasts[a]

$$Prob\left(E^{M}_{jtw} < E^{I}_{jtw}\right) = \alpha_0 + \alpha_1 DAGE_{jtw} + \alpha_2 lnMV_{jtw} + \alpha_3 \hat{\rho}_{jtw} + \sum_{w=2}^{W} \lambda_w WD_w + \sum_{t=2}^{T} \delta_t YD_t + \varepsilon_{jtw}$$

Model		$\hat{\alpha}_0$ (p-value)[b]	$\hat{\alpha}_1$ (p-value)[b]	$\hat{\alpha}_2$ (p-value)[b]	$\hat{\alpha}_3$ (p-value)[b]	Forecast Window Dummy Vars.	Year Dummy Vars.	Goodness of Fit L. R. Chi-Sq. (p-value)[b]
1	Equation (8) of paper	-0.01 (0.86)	-0.01 (<0.01)	0.02 (<0.01)		Yes	Yes	20,105 (<0.01)
2		0.49 (<0.01)	-0.01 <0.01)		-0.56 (<0.01)	Yes	Yes	19,344 (<0.01)
3		0.48 (<0.01)	0.01 (<0.01)	<0.01 (0.85)	-0.56 (<0.01)	Yes	Yes	19,793 (<0.01)
4		0.44 (<0.01)	0.01 (<0.01)	<-0.01 (0.84)	-0.56 (<0.01)	Yes	No	19,504 (<0.01)
5		0.46 (<0.01)	0.01 (<0.01)	<-0.01 (0.44)	-0.56 (<0.01)	No	No	19,508 (<0.01)

E^{M}_{jtw} is the absolute error in the mean forecast for firm *j* in year *t*, during forecast window *w*; and E^{I}_{jtw} is the absolute error in the most recent individual forecast for firm *j* in year *t*, during forecast window *w*. A dummy variable is created coded one when $E^{M}_{jtw} < E^{I}_{jtw}$ and zero otherwise.

$DAGE_{jtw}$ is the difference (in days) between the age of the most recent individual forecast and the mean age of the forecasts comprising the mean forecast for firm *j* in year *t*, during forecast window *w*.

$lnMV_{jtw}$ is the natural log of market value (deflated to 1985 CPI dollars) at the end of the fiscal year for firm *j* in year *t*, during forecast window *w*.

$\hat{\rho}_{jtw}$ is BKLS consensus (the across-analyst correlation in forecast errors) for firm *j* in year *t*, during forecast window *w*.

YD_t are a set of year dummy variables equal to one for year *t* and zero for all other years.

WD_w are a set of forecast window dummy variables equal to one for forecast window *w* and zero for all other forecast windows.

a The dependent variable is coded one if the mean forecast is more accurate than the most recent individual forecast, and zero otherwise

b 2-tailed chi-squared p-value.

FIGURE 1
Larger Vs. Smaller Firms
(Sample Size Varies)