Do Investors Respond to Analysts’ Forecast Revisions as if Forecast Accuracy Is All That Matters?

Michael B. Clement
Senyo Y. Tse
The University of Texas at Austin

ABSTRACT: Prior research suggests that investors’ response to analyst forecast revisions increases with the analyst’s forecast accuracy. We extend this research by examining whether investors appear to extract all of the information that analyst characteristics provide about forecast accuracy. We find that only some of the analyst characteristics that are associated with future forecast accuracy are also associated with return responses to forecast revisions. This suggests that investors fail to extract some of the information that analyst characteristics can provide about future forecast accuracy. In addition, forecast properties other than expected accuracy appear to be value-relevant. For example, investors respond more strongly to forecasts released earlier in the year and to forecasts by analysts employed by large brokerages than appears warranted by the ability of forecast timeliness and broker size to predict forecast accuracy. We conclude that investors respond to analysts’ forecast revisions as if forecast accuracy is not all that matters.

Keywords: analyst forecast accuracy; analyst characteristics; security returns.

Data Availability: Data are available from public sources.

I. INTRODUCTION

Theory predicts that investors’ response to forecast revisions increases with the expected accuracy of the forecast (Abarbanell et al. 1995), and empirical research documents results...
consistent with this prediction (Stickel 1992; Park and Stice 2000; Gleason and Lee 2003). Empirical research also finds an association between forecast accuracy and several forecast and analyst characteristics: forecast timeliness, analyst experience, broker size, and the number of firms and industries the analyst follows (Mikhail et al. 1997; Clement 1999; Jacob et al. 1999). Our study investigates whether \textit{ex ante} predicted forecast accuracy is sufficient to explain differences in investors’ response to analyst forecast revisions. If so, then individual analyst characteristics should be associated with returns only to the extent that those characteristics predict forecast accuracy. Implicitly, investors would use all relevant analyst characteristics to predict forecast accuracy, and then would respond to each forecast revision according to the analyst’s expected forecast accuracy. Analyst characteristics that are associated with increased forecast accuracy would therefore also be associated with greater return responses to forecast revisions.

There are at least three reasons, however, why the weights investors place on forecasts may diverge from the weights suggested by a model that uses individual analyst characteristics to predict forecast accuracy. First, factors other than forecast accuracy may be value-relevant. For example, investors may respond more strongly to forecasts issued early in the fiscal year (timely forecasts) even though those early forecasts are generally less accurate than later forecasts. As Schipper (1991, 113) notes:

\begin{quote}
To the extent having the forecast sooner (even at the cost of less accuracy) implies greater investing profits to consumers of analysts’ earnings forecasts, the loss function implied by pleasing customers will create a preference for timeliness.
\end{quote}

Second, investors may find it more efficient to rely on readily observable characteristics (such as the status of the brokerage employing the analyst) as proxies for the accuracy of the forecast, rather than attempting to identify accurate analysts by monitoring analyst characteristics. In this case, analyst affiliation could be more strongly associated with return responses to forecast revisions than would be suggested by the effect of broker affiliation on predicted forecast accuracy alone.

Third, prior research shows that investors do not always weight information rationally in relation to its ability to predict future earnings. For example, prior studies show that investors appear to undervalue cash flows, and to overvalue accruals (Sloan 1996) and abnormal accruals (Xie 2001), relative to their ability to predict earnings. Similarly, Elgers et al. (2001) find that investors appear to undervalue the information in analysts’ annual earnings forecasts for predicting future earnings. Therefore, it is an empirical question whether the weights investors appear to place on forecasts diverge from the weights suggested by a model that predicts forecast accuracy.

This study extends prior research by conducting a more complete examination of the association between analyst accuracy and return responses to forecast revisions. Specifically, we examine whether investors respond to analysts’ forecast revisions as if forecast accuracy

---

1 In our study, \textit{timeliness} refers to how early or late the forecast date is in the fiscal period. Forecasts made earlier in the year are more timely and have longer horizons. The other predictors of forecast accuracy (firm-specific experience, broker size, forecast frequency, number of firms and industries followed) are analyst characteristics rather than forecast characteristics. For conciseness, we refer to the full set of potential explanatory variables, including forecast timeliness, as \textit{analyst characteristics}.

2 Our goal is to test whether price reactions to analyst forecasts suggest that investors weight forecasts based on rational predictions of forecast accuracy. We do not hypothesize or test market efficiency except in this narrow sense. Furthermore, evidence that investors do not focus solely on predicted forecast accuracy when responding to forecast revisions need not imply market inefficiency. For example, more timely but less accurate forecasts may provide useful information to investors. The consistency of return responses with market efficiency is an interesting issue for future research.
is all that matters. We investigate the stock market’s response to individual analysts’ forecast revisions using a two-stage rational expectations procedure adapted from Mishkin (1983). In the first stage, we simultaneously estimate two models. First we estimate a forecast accuracy model to obtain a rational expectations prediction of analyst forecast accuracy. Rational expectations implies that investors use all available information to predict forecast accuracy, so our forecast accuracy model incorporates a broad set of explanatory variables identified in prior research, as well as a new variable that we expect to be associated with forecast accuracy (days elapsed since the prior forecast). We then estimate a valuation model that regresses the return response to a forecast revision on the magnitude of the forecast revision, weighted by the forecasting analyst’s predicted forecast accuracy (from the forecast accuracy model). That is, we constrain the returns model coefficients to equal the forecast accuracy model coefficients. In the second stage, we estimate an unconstrained returns model that removes the forecast-accuracy-related constraints on estimated coefficients. We then determine whether the coefficients on analyst characteristics differ significantly across the constrained and unconstrained returns models. This procedure enables us to infer whether investors respond to forecast revisions as if they weight those revisions in proportion to the analyst’s expected forecast accuracy.

We find that the implied weights on the characteristics differ significantly across the constrained and unconstrained returns models. Specifically, security return responses are greater for timely (early) forecasts than for later forecasts, even though timely forecasts are generally less accurate than later forecasts. Sensitivity analysis incorporating a proxy for the level of uncertainty suggests that return responses to timely forecasts are stronger because there is greater uncertainty about earnings early in the year. Return responses to forecast revisions also increase with days elapsed since the prior forecast, even though these forecasts are, on average, less accurate than forecasts issued shortly after the prior forecast. In addition, forecasts provided by analysts employed by larger brokers are associated with greater return responses than would be predicted by those forecasters’ accuracy alone. This result suggests that investors may use analyst affiliation as a signal of forecast accuracy, consistent with the findings of Hong and Kubik (2003). These results hold only for high-innovation forecasts—forecasts that are above both the analyst’s prior forecast and the consensus forecast, or else are below both the analyst’s prior forecast and the consensus (Gleason and Lee 2003). In contrast, for the remaining (low-innovation) forecast revisions, we find that the return response is not significantly related to any of the analyst characteristics that are predictive of forecast accuracy.

Our results make three contributions to the existing literature. First, we document that a broad set of analyst and forecast characteristics contributes simultaneously to explaining analyst forecast accuracy. Brown (2001) finds that past performance better predicts forecast accuracy than several analyst characteristics combined (general experience, company-specific experience, the number of companies and industries the analyst follows, and brokerage size). However, we find that a variable Brown (2001) omits—forecast frequency—and which Jacob et al. (1999) use to proxy the amount of effort the analyst devotes to following the company, is just as important as past accuracy for explaining future accuracy. Second, we show that forecast accuracy is not the sole determinant of security return responses to analyst forecast revisions. For example, returns respond more strongly to revisions by analysts employed by large brokerages than seems warranted by those analysts’ forecast accuracy. On the other hand, forecast frequency, firm experience, and the number of companies and industries the analyst follows are associated with forecast accuracy, but not with the security price response to forecast revisions. More surprisingly, the forecast horizon and days elapsed since the last forecast are significantly negatively associated with
forecast accuracy, but are positively associated with return responses, i.e., in a direction opposite to the forecast accuracy predictions. Third, we provide evidence on Schipper’s (1991) questions about how investors trade off accuracy and timeliness; our results suggest that timeliness is important to investors even at the cost of accuracy.\textsuperscript{3} Collectively, these results suggest that investors do \textit{not} respond to analyst forecasts as if forecast accuracy is all that matters.

Our results also have implications for identifying proxies for expected earnings. The most common proxy, the mean forecast, implicitly assumes that investors weight all analysts’ forecasts equally when forming expectations. However, our results suggest that investors apply different weights to individual forecasts. Researchers could use these weights to derive consensus forecasts that are closer to investors’ expectations than the mean forecast. Managers could use the weights to more accurately identify investors’ expectations in order to implement more effective disclosure strategies. For example, if investors rely heavily on forecasts of analysts employed by large brokers, then managers could compare their private information about upcoming earnings to those specific analysts’ forecasts when deciding whether to make voluntary disclosures that may influence current expectations. Our results also have implications for evaluating analysts’ performance. For example, the \textit{Wall Street Journal} rates analysts based solely on forecast accuracy, but our results suggest that timeliness is also important to investors.

We organize the remainder of the paper as follows. Section II discusses prior literature that investigates the association between analysts’ characteristics and forecast accuracy. Section III outlines the research design, Section IV discusses the results, and Section V summarizes our conclusions.

\section*{II. ANALYST-CHARACTERISTICS LITERATURE}

Prior research documents that forecast frequency, broker size, general and firm-specific experience, and the number of companies and industries the analyst follows are associated with forecast accuracy. Jacob et al. (1999) find that forecast accuracy increases with forecast frequency (a proxy for the amount of effort the analyst devotes to following a company), even after controlling for forecast timeliness. Clement (1999) and Jacob et al. (1999) find that analysts employed by larger brokers issue more accurate forecasts on average. Analysts who issue more accurate forecasts are more likely to move to a high-status (i.e., large and prestigious) brokerage firm, and high-status brokers are more likely than other employers to dismiss an analyst for poor forecasting performance (Hong and Kubik 2003). Mikhail et al. (1997) and Jacob et al. (1999) find that forecast accuracy increases as analysts gain firm-specific experience, but they find no association for general forecasting experience. Clement (1999) finds that forecast accuracy increases with both firm-specific and general forecasting experience, although he finds that an additional year of firm-specific forecasting experience is associated with greater improvement in forecast accuracy than is an additional year of general forecasting experience. Jacob et al. (1999) and Clement (1999) also find that forecast accuracy declines as analysts follow more companies and industries.

Brown (2001) extends prior studies by investigating how well all of the abovementioned analyst characteristics—except forecast frequency—predict forecast accuracy. He finds that

\textsuperscript{3} Analysts’ role in setting stock prices may well have changed since the passage of Regulation Full Disclosure (FD). Prior to FD there is evidence that managers guided analysts (Matsumoto 2002), and so analysts’ forecast revisions may have reflected managers’ private information. If this guidance increased the value-relevance of analysts’ forecast revisions, then analysts’ forecast revisions may be less informative to investors in the post-FD environment, and our inferences may therefore no longer hold in that environment. Whether the informativeness of analysts’ forecast revisions has changed with FD is an empirical question, and so far the results are mixed (Mohanram and Sunder 2002; Zitewitz 2002; Agrawal and Chadra 2002; Heffin et al. 2003).
each characteristic provides incremental predictive power for forecast accuracy beyond past forecasting performance, although the analyst’s past forecasting performance has greater predictive power than all of the other analyst characteristics combined. Thus, our forecast accuracy model includes characteristics in addition to past forecast accuracy because past accuracy is a noisy measure of forecasting ability. For example, able forecasters occasionally make a large error, and inept forecasters sometimes forecast accurately simply by chance.

Although several studies investigate the association between analyst characteristics and forecast accuracy, we know of no prior evidence on whether investor responses to forecast revisions are consistent with rational estimates of analyst forecast accuracy. The following section outlines our hypotheses and research design for investigating this question.

III. SPECIFICATION OF EMPIRICAL TESTS

Analysts’ Characteristics and Forecast Accuracy

To determine the association between analyst characteristics and forecast accuracy we begin with Brown’s (2001) model of forecast accuracy as a function of firm-specific experience, broker size, prior forecast accuracy, forecast horizon, and the number of companies and industries the analyst follows. We add to this model forecast frequency (Jacob et al. 1999) and a new variable: days elapsed since the last forecast. Forecasts that are made long after the prior forecast are likely to reflect new information that was not incorporated in prior forecasts. We describe the variables in greater detail below.

To facilitate comparisons of estimated coefficients across different determinants of forecast accuracy within the forecast accuracy model, and between coefficients in the forecast accuracy and stock returns models, we standardize all analyst and forecast characteristics to lie between 0 and 1. The original minimum and maximum values for each explanatory variable correspond to transformed values of 0 and 1, respectively. For each analyst characteristic and analyst i, the standardized independent variables take the form:

\[
\text{CHARACTERISTIC}_{ijt} = \frac{\text{RAW\_CHARACTERISTIC}_{ijt} - \text{RAW\_CHARACTERISTIC}_{\text{min}\_jt}}{\text{RAW\_CHARACTERISTIC}_{\text{max}\_jt} - \text{RAW\_CHARACTERISTIC}_{\text{min}\_jt}},
\]

where RAW\_CHARACTERISTIC\_max\_jt and RAW\_CHARACTERISTIC\_min\_jt are the original maximum and minimum values, respectively, of a characteristic for firm j in year t. A high value for CHARACTERISTIC\_ijt indicates that analyst i scores high on that characteristic relative to other analysts who follow firm j in year t. Our standardization results in a relative measure for all analysts who followed the same firm during the same time period.4

To obtain measures of forecasting performance that increase with forecast accuracy, we standardize the forecast accuracy measure to be 0 for the least accurate forecast (highest absolute forecast error) and 1 for the most accurate forecast (lowest absolute forecast error). The standardized accuracy measure for analyst i takes the form:

\[
\text{ACCURACY}_{ijt} = \frac{\text{ACTUAL}_{ijt} - \text{PREDICT}_{ijt}}{\text{MAX}\_ERROR - \text{MIN}\_ERROR},
\]

where ACTUAL\_ijt and PREDICT\_ijt are the actual and predicted forecast errors, respectively, and MAX\_ERROR and MIN\_ERROR are the maximum and minimum forecast errors, respectively, for the analyst over the period.5

4 Using dummy variables to specify whether an observation is above or below its mean retains less information about variation in the variables than the approach we use. Nonetheless, we obtain similar results using the dummy variable approach.

5 As an example, suppose analyst i follows 20 companies and the minimum and maximum number of companies followed by analysts who follow firm j in year t are 5 and 25, respectively. Then analyst i falls at the 75 percent level [(20 – 5)/(25 – 5)] of the range of companies followed by analysts who followed firm j in year t.
where \( \text{AFE}_{\text{max}}_{jt} \) and \( \text{AFE}_{\text{min}}_{jt} \) are the maximum and minimum absolute forecast errors, respectively, for analysts following firm \( j \) in year \( t \). Higher values for \( \text{ACCURACY}_{ijt} \) therefore indicate that the analyst is more accurate.

**Analyst Characteristics and Stock Market Responses**

If investors respond to an analyst’s forecast revisions without considering the predicted accuracy of that analyst’s forecast, then we can model investors’ return response as:

\[
\text{CAR}_{ijt} = \delta_0 + \delta_1 \text{REVP}_{ijt} + \epsilon_{ijt},
\]

where \( \text{CAR}_{ijt} \) (cumulative abnormal return) is the three-trading-day cumulative market-adjusted abnormal return surrounding analyst \( i \)’s earnings forecast revision for firm \( j \) in year \( t \). The accumulation period starts one day before the revision and ends one day after the revision. We compute the return by subtracting value-weighted market returns from firm \( j \)’s return. \( \text{REVP}_{ijt} \) (revision scaled by price) is analyst \( i \)’s forecast revision for firm \( j \) in year \( t \) scaled by the end-of-day stock price two days prior to the revision. The revision equals analyst \( i \)’s forecast of firm \( j \)’s earnings in year \( t \), less analyst \( i \)’s prior forecast of firm \( j \)’s earnings in year \( t \).

If, however, investors respond to forecast revisions based on the analyst’s predicted accuracy, then we can model investor response to forecast revisions as:

\[
\text{CAR}_{ijt} = \gamma_0 + \gamma_1 \text{REVP}_{ijt} \times \text{ACCURACY}_{ijt}^r + \epsilon_{ijt},
\]

where \( \text{ACCURACY}_{ijt}^r \) = the predicted accuracy of the forecast revision.

Since future accuracy is unknown when the analyst issues a forecast, investors must use information available at the time of the forecast to estimate its accuracy. We predict that the analyst’s forecasting performance improves with prior forecasting performance, broker size, forecast frequency, and experience forecasting for that firm, and decreases with days elapsed since the last forecast, forecast horizon, and the number of companies and industries the analyst follows:

\[
\text{ACCURACY}_{ijt} = \alpha_0 + \alpha_1 \text{DAYS_ELAPSED}_{ijt} + \alpha_2 \text{FOR}_{\text{HORIZON}}_{ijt} + \alpha_3 \text{LAG}_{\text{ACCURACY}}_{ijt} + \alpha_4 \text{BROKER}_{\text{SIZE}}_{ijt} + \alpha_5 \text{FOR}_{\text{FREQUENCY}}_{ijt} + \alpha_6 \text{FIRM}_{\text{EXPERIENCE}}_{ijt} + \alpha_7 \text{COMPANIES}_{ijt} + \alpha_8 \text{INDUSTRIES}_{ijt} + \epsilon_{ijt},
\]

---

6 Because analysts issue forecasts throughout the year, it is unlikely that returns around forecast revisions are systematically related to other events. In particular, the returns are not likely to be due to management forecasts, which occur infrequently. Using the First Call database, we find 7,581 management forecasts of earnings for 2,899 firms from January 1993 to March 1998, an average of one management forecast every two years for each firm. In contrast, we find 265,620 analyst forecasts for 11,238 firms on the I/B/E/S database for about the same period, even after we restrict the sample to one forecast per analyst per year.

7 We measure forecast revisions relative to the analyst’s own prior forecast because that measure is more strongly correlated with returns than are revisions measured relative to the consensus forecast. Gleason and Lee (2003) find similar results, and recommend measuring forecast revisions relative to the analyst’s own prior forecast. However, measuring the revision relative to the consensus forecast leads to identical inferences.
where:

\[ ACCURACY_{ijt} = \text{a measure of analyst i’s forecast accuracy for firm j in year t.}\]

\[ \text{It is calculated as the maximum absolute forecast error for analysts who follow firm j in year t minus the absolute forecast error of analyst i following firm j in year t, with this difference scaled by the range of absolute forecast errors for analysts following firm j in year t;} \]

\[ DAYS\_ELAPSED_{ijt} = \text{a measure of the days elapsed since the last forecast by any analyst following firm j in year t. It is calculated as the days between analyst i’s forecast of firm j’s earnings in year t and the most recent preceding forecast of firm j’s earnings by any analyst, minus the minimum number of days between two adjacent forecasts of firm j’s earnings by any two analysts in year t, with this difference scaled by the range of days between two adjacent forecasts of firm j’s earnings in year t;} \]

\[ FOR\_HORIZON_{ijt} = \text{a measure of the time from the forecast date to the end of the fiscal period. It is calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst i following firm j in year t minus the minimum forecast horizon for analysts who follow firm j in year t, with this difference scaled by the range of forecast horizons for analysts following firm j in year t;} \]

\[ LAG\_ACCURACY_{ijt} = \text{a measure of analyst i’s prior forecast accuracy for firm j. It is calculated as the maximum ACCURACY for analysts who follow firm j in year t – 1 minus the ACCURACY for analyst i following firm j in year t – 1, with this difference scaled by the range of ACCURACY for analysts following firm j in year t – 1;} \]

\[ BROKER\_SIZE_{ijt} = \text{a measure of the analyst’s broker size. It is calculated as the number of analysts employed by the broker employing analyst i following firm j in year t minus the minimum number of analysts employed by brokers for analysts following firm j in year t, with this difference scaled by the range of brokerage size for analysts following firm j in year t;} \]

\[ FOR\_FREQUENCY_{ijt} = \text{a measure of analyst i’s forecast frequency for firm j. It is calculated as the number of firm-j forecasts made by analyst i following firm j in year t minus the minimum number of firm-j forecasts for analysts following firm j in year t, with this difference scaled by the range of number of firm-j forecasts issued by analysts following firm j in year t;} \]

\[ FIRM\_EXPERIENCE_{ijt} = \text{a measure of analyst i’s firm-specific experience. It is calculated as the number of years of firm-specific experience for analyst i following firm j in year t minus the minimum number of years of firm-specific experience for analysts following firm j in year t, with this difference scaled by the range of years of firm-specific experience for analysts following firm j in year t;} \]
COMPANIES$_{ijt}$ is a measure of the number of companies analyst $i$ follows in year $t$. It is calculated as the number of companies followed by analyst $i$ following firm $j$ in year $t$ minus the minimum number of companies followed by analysts who follow firm $j$ in year $t$, with this difference scaled by the range in the number of companies followed by analysts following firm $j$ in year $t$; and INDUSTRIES$_{ijt}$ is a measure of the number of industries analyst $i$ follows in year $t$. It is calculated as the number of two-digit SICs followed by analyst $i$ following firm $j$ in year $t$ minus the minimum number of two-digit SICs followed by analysts who follow firm $j$ in year $t$, with this difference scaled by the range in the number of two-digit SICs followed by analysts following firm $j$ in year $t$.

We refer to Equation (3) as the forecast accuracy model.

Substituting the predicted forecast accuracy from Equation (3) into Equation (2) yields the returns model:

\[
\text{CAR}_{ijt} = \gamma_0 + \gamma_1 \text{REVP}_{ijt} \times (\alpha_0^* + \alpha_1^* \text{DAYS}_\text{ELAPSED}_{ijt} + \alpha_2^* \text{FOR}_\text{HORIZON}_{ijt} \\
+ \alpha_3^* \text{LAG}_\text{ACCURACY}_{ijt} + \alpha_4^* \text{BROKER}_\text{SIZE}_{ijt} \\
+ \alpha_5^* \text{FOR}_\text{FREQUENCY}_{ijt} + \alpha_6^* \text{FIRM}_\text{EXPERIENCE}_{ijt} \\
+ \alpha_7^* \text{COMPANIES}_{ijt} + \alpha_8^* \text{INDUSTRIES}_{ijt} ) + \epsilon_{ijt},
\]

where the $\alpha_i^*$ are the returns model coefficients corresponding to the forecast model coefficients ($\alpha_i$) for each analyst characteristic in Equation (3). We refer to Equation (4) as the valuation model.

Using the method outlined in Mishkin (1983), we estimate the forecast accuracy and valuation models in two stages using iterative weighted nonlinear least squares. In the first stage of the model we constrain $\alpha_i^* = \alpha_i$. In the second stage we reestimate Equation (4) and allow the coefficients to vary freely. If investor responses to forecast revisions reflect the ability of analyst characteristics to predict forecast accuracy, then $\alpha_i^*$ should equal $\alpha_i$.

---

8 Sloan (1996) introduced the Mishkin (1983) model to accounting research in his study investigating whether investor responses to earnings are consistent with rational expectations, based on the ability of cash flow and accruals to predict next-period income. Xie (2001) and Elgers et al. (2001) also use the Mishkin model to study the consistency of returns with rational expectations of earnings from abnormal accruals and analyst forecasts, respectively. We also estimated the forecast accuracy model and the constrained and unconstrained returns models (Equations [3] and [4]) using ordinary least squares (OLS), and tested the constraint on the returns model coefficients. Both the OLS and Mishkin approaches yield qualitatively similar results. We conclude that the study’s results are not induced by the Mishkin approach.

9 This second stage can be written as the OLS model:

\[
\text{CAR}_{ijt} = \delta_0 + \beta_0 \text{REVP}_{ijt} + \beta_1 \text{REVP}_{ijt} \times \text{DAYS}_\text{ELAPSED}_{ijt} \\
+ \beta_2 \text{REVP}_{ijt} \times \text{FOR}_\text{HORIZON}_{ijt} + \beta_3 \text{REVP}_{ijt} \times \text{LAG}_\text{ACCURACY}_{ijt} \\
+ \beta_4 \text{REVP}_{ijt} \times \text{BROKER}_\text{SIZE}_{ijt} + \beta_5 \text{REVP}_{ijt} \times \text{FOR}_\text{FREQUENCY}_{ijt} \\
+ \beta_6 \text{REVP}_{ijt} \times \text{FIRM}_\text{EXPERIENCE}_{ijt} + \beta_7 \text{REVP}_{ijt} \times \text{COMPANIES}_{ijt} \\
+ \beta_8 \text{REVP}_{ijt} \times \text{INDUSTRIES}_{ijt} + \epsilon_{ijt},
\]

where $\alpha_i^* = \beta_i / \gamma_1$, but we derive our results by jointly estimating Equations (3) and (4) using the Mishkin procedure.
for all characteristics in the unconstrained returns model. In contrast, if the weights investors place on analyst characteristics when responding to forecast revisions differ from the characteristics’ association with forecast accuracy, then the coefficients will differ between the constrained and unconstrained returns models.\(^{10}\)

We assess the difference between coefficients in the constrained and unconstrained returns models using the following likelihood-ratio statistic, which is distributed asymptotically as \(\chi^2(q) = -2n \log \left( \frac{SSR_c}{SSR_u} \right)\), where \(q\) is the number of constraints; \(n\) is the number of observations; \(SSR_c\) is the sum of squared residuals from the constrained estimation; and \(SSR_u\) is the sum of squared residuals from the unconstrained estimation.

**IV. SAMPLE SELECTION AND RESULTS**

**Sample Selection**

Discussions with I/B/E/S officials indicated that prior to the early 1990s, the forecast release date I/B/E/S recorded often differed from the actual forecast date by a few days, but that the accuracy of the forecast dates improved in the early 1990s. Clearly, we need accurate release dates to measure return responses to the forecast revisions. Thus, our sample includes annual earnings forecasts from the I/B/E/S data set for the period 1994–1998.

We restrict the sample to forecasts made at least 30 days, but not more than one year, before the end of the accounting period (so the minimum forecast horizon is 30 days). Consistent with other studies (e.g., O’Brien 1990; Sinha et al. 1997; Clement 1999), we retain only the last forecast for each analyst-firm pair during the period.\(^{11}\) We obtain returns data from CRSP. We eliminate observations from the sample if (1) there are no CRSP returns data around the forecast revision, (2) the analyst did not issue a forecast in the prior year for the firm (the analyst’s prior forecast performance is an independent variable in the model), (3) the scaled forecast revision is in the top or bottom 1 percent of revisions, or (4) only one analyst follows the firm. The last requirement is necessary because we measure an analyst’s characteristics and forecast accuracy relative to other analysts who follow the same firm.\(^{12}\)

**Results**

**Descriptive Statistics**

Table 1 reports summary statistics for the sample. Panel A shows the distributions of the raw (untransformed) variables. The distributions are consistent with those reported for similar variables in other studies (Clement 1999; Jacob et al. 1999). For example, forecasts precede the fiscal year-end by 97 days, on average (recall that our minimum forecast horizon is 30 days). Each analyst provides about four forecasts for each firm in a given year, and analysts follow an average of 20 firms in five industries. The median values of the firm characteristics are generally different from the means, indicating that the distributions of

\(^{10}\) The test described is valid even if the forecasting equation is incomplete, as Mishkin (1983, 45–46) explains: “Thus leaving out relevant variables from the OLS regression...will not affect the rationality implication that \(\alpha_t - \alpha^*\) should not differ significantly from zero.” He goes on to state that the above procedure tests rationality no matter what available past information is included in or excluded from the forecasting equation. Sloan (1996, 302, footnote 13) makes a similar point.

\(^{11}\) Because our objective is to determine whether investors respond to characteristics that are associated with systematic differences in forecast accuracy, we need only one analyst-firm pair for each analyst-firm-year. Prior studies (e.g., Clement 1999; Brown 2001) suggest that this sample selection method identifies samples with systematic differences in forecast accuracy.

\(^{12}\) Restricting the sample to firms with forecasts from a minimum of three or four analysts per firm instead of two does not affect our inferences.
TABLE 1
(n = 35,351)

Panel A: Distribution of Selected Analyst Characteristics before Standardization

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units of Measurement</th>
<th>Mean</th>
<th>25th Percentile</th>
<th>Median</th>
<th>75th Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>Days from prior forecast</td>
<td>13.6</td>
<td>2</td>
<td>6</td>
<td>16</td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>Days to fiscal year-end</td>
<td>97.0</td>
<td>57</td>
<td>71</td>
<td>131</td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>Number of analysts</td>
<td>33.8</td>
<td>12</td>
<td>29</td>
<td>49</td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>Number of forecasts</td>
<td>3.8</td>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>Years</td>
<td>3.9</td>
<td>2</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>COMPANIES</td>
<td>Companies followed</td>
<td>19.5</td>
<td>11</td>
<td>16</td>
<td>23</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>Industries followed</td>
<td>5.4</td>
<td>3</td>
<td>5</td>
<td>7</td>
</tr>
</tbody>
</table>

Panel B: Distribution of Analyst Characteristics after Standardization

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>25th Percentile</th>
<th>Median</th>
<th>75th Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCURACY</td>
<td>0.58</td>
<td>0.06</td>
<td>0.71</td>
<td>1.00</td>
</tr>
<tr>
<td>DAYS_ELAPSED</td>
<td>0.38</td>
<td>0.00</td>
<td>0.20</td>
<td>0.82</td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>0.38</td>
<td>0.03</td>
<td>0.20</td>
<td>0.82</td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>0.57</td>
<td>0.00</td>
<td>0.67</td>
<td>1.00</td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>0.43</td>
<td>0.05</td>
<td>0.35</td>
<td>0.82</td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>0.42</td>
<td>0.00</td>
<td>0.33</td>
<td>0.80</td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>0.36</td>
<td>0.00</td>
<td>0.20</td>
<td>0.71</td>
</tr>
<tr>
<td>COMPANIES</td>
<td>0.41</td>
<td>0.05</td>
<td>0.30</td>
<td>0.75</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>0.40</td>
<td>0.00</td>
<td>0.29</td>
<td>0.75</td>
</tr>
</tbody>
</table>

(continued on next page)
TABLE 1 (continued)

Panel C: Pearson Correlations among Analyst Characteristics (Significance levels are in parentheses)

<table>
<thead>
<tr>
<th></th>
<th>DAYS_ELAPSED</th>
<th>FOR_HORIZON</th>
<th>LAG_ACCURACY</th>
<th>BROKER_SIZE</th>
<th>FOR_FREQUENCY</th>
<th>FIRM_EXPERIENCE</th>
<th>COMPANIES</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>-0.047</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>-0.251</td>
<td>0.055</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>0.084</td>
<td>-0.034</td>
<td>-0.042</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>0.019</td>
<td>0.036</td>
<td>0.032</td>
<td>0.020</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>0.146</td>
<td>0.060</td>
<td>-0.339</td>
<td>0.033</td>
<td>0.017</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td>(0.260)</td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>0.019</td>
<td>0.001</td>
<td>-0.018</td>
<td>0.003</td>
<td>-0.002</td>
<td>0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td>(0.822)</td>
<td>(&lt;0.001)</td>
<td>(0.607)</td>
<td>(0.755)</td>
<td>(&lt;0.001)</td>
<td></td>
</tr>
<tr>
<td>COMPANIES</td>
<td>-0.036</td>
<td>0.023</td>
<td>-0.017</td>
<td>-0.055</td>
<td>0.007</td>
<td>-0.008</td>
<td>0.154</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td>(0.002)</td>
<td>(&lt;0.001)</td>
<td>(0.159)</td>
<td>(0.139)</td>
<td>(&lt;0.001)</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>-0.040</td>
<td>0.010</td>
<td>-0.000</td>
<td>-0.050</td>
<td>-0.118</td>
<td>-0.035</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>(&lt;0.001)</td>
<td>(0.065)</td>
<td>(0.947)</td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td>(&lt;0.001)</td>
<td>(0.544)</td>
</tr>
</tbody>
</table>

(continued on next page)
TABLE 1 (continued)

"We omit forecast accuracy from Panel A because the unstandardized variable (absolute per-share forecast error) is not directly comparable among firms. We report descriptive statistics for standardized forecast errors in Panel B.

\[ \text{ACCURACY}_{ijt} \] a measure of analyst i’s forecast accuracy for firm j in year t. It is calculated as the maximum absolute forecast error for analysts who follow firm j in year t minus the absolute forecast error of analyst i following firm j in year t, with this difference scaled by the range of absolute forecast errors for analysts following firm j in year t;

\[ \text{DAYS \_ELAPSED}_{ijt} \] a measure of the days elapsed since the last forecast by any analyst following firm j in year t. It is calculated as the days between analyst i’s forecast of firm j’s earnings in year t and the most recent preceding forecast of firm j’s earnings by any analyst, minus the minimum number of days between two adjacent forecasts of firm j’s earnings by any two analysts in year t, with this difference scaled by the range of days between two adjacent forecasts of firm j’s earnings in year t;

\[ \text{FOR\_HORIZON}_{ijt} \] a measure of the time from the forecast date to the end of the fiscal period. It is calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst i following firm j in year t minus the minimum forecast horizon for analysts who follow firm j in year t, with this difference scaled by the range of forecast horizons for analysts following firm j in year t;

\[ \text{LAG\_ACCURACY}_{ijt} \] a measure of analyst i’s prior forecast accuracy for firm j. It is calculated as the maximum ACCURACY for analysts who follow firm j in year t minus 1 minus the ACCURACY for analyst i following firm j in year t minus 1, with this difference scaled by the range of ACCURACY for analysts following firm j in year t minus 1;

\[ \text{BROKER\_SIZE}_{ijt} \] a measure of the analyst’s broker size. It is calculated as the number of analysts employed by the broker employing analyst i following firm j in year t minus the minimum number of analysts employed by brokers for analysts following firm j in year t, with this difference scaled by the range of brokerage size for analysts following firm j in year t;

\[ \text{FOR\_FREQUENCY}_{ijt} \] a measure of analyst i’s forecast frequency for firm j. It is calculated as the number of firm-j forecasts made by analyst i following firm j in year t minus the minimum number of firm-j forecasts for analysts following firm j in year t, with this difference scaled by the range of number of firm-j forecasts issued by analysts following firm j in year t;

\[ \text{FIRM\_EXPERIENCE}_{ijt} \] a measure of analyst i’s firm-specific experience. It is calculated as the number of years of firm-specific experience for analyst i following firm j in year t minus the minimum number of years of firm-specific experience for analysts following firm j in year t, with this difference scaled by the range of years of firm-specific experience for analysts following firm j in year t;

\[ \text{COMPANIES}_{ijt} \] a measure of the number of companies analyst i follows in year t. It is calculated as the number of companies followed by analyst i following firm j in year t minus the minimum number of companies followed by analysts who follow firm j in year t, with this difference scaled by the range in the number of companies followed by analysts following firm j in year t; and

\[ \text{INDUSTRIES}_{ijt} \] a measure of the number of industries analyst i follows in year t. It is calculated as the number of two-digit SICs followed by analyst i following firm j in year t minus the minimum number of two-digit SICs followed by analysts who follow firm j in year t, with this difference scaled by the range in the number of two-digit SICs followed by analysts following firm j in year t."
the characteristics are asymmetric. Panel B shows the distributions of the variables in Panel A, standardized to lie between 0 and 1. This transformation preserves the relative values of the explanatory variables while reducing the influence of extreme observations.13

Panel C of Table 1 reports correlations among the variables. All of the correlations between the analyst characteristics and forecast accuracy are significant in the expected directions at better than the 1 percent level. The characteristics that are associated with greater forecast accuracy are (from highest to lowest correlation) forecast frequency, lagged forecast accuracy, broker size, and firm-specific experience. The characteristics that are associated with lower forecast accuracy are (from the most negative to the least negative correlation) forecast horizon, days elapsed since the last forecast, number of industries the analyst follows, and number of companies the analyst follows. The number of companies and industries the analyst follows are highly positively correlated, while forecast frequency is negatively correlated with forecast horizon. The positive correlation between firm experience and companies followed suggests that more experienced analysts follow more firms. The negative correlation between broker size and industries followed suggests that larger brokerages permit greater specialization among their analyst employees.

Tests of Association between Analysts’ Characteristics and Forecast Accuracy

Panel A of Table 2 reports the results of estimating the forecast accuracy model (Equation [3]). Consistent with the correlations in Table 1, the regression results show that an analyst’s accuracy (relative to that of other analysts forecasting the same firm’s earnings in the same year) increases with prior accuracy, broker size, forecast frequency, and firm experience, and decreases with days elapsed since the last forecast, forecast horizon, and the number of companies and industries the analyst follows. These results are generally consistent with prior studies, indicating that our transformation of the variables to lie between 0 and 1 preserves the information in analyst forecasts and characteristics. However, our results yield two new insights. First, whereas Brown (2001) finds that past forecast accuracy dominates individual analyst characteristics in explaining current forecast accuracy, we find that a variable Brown (2001) omits—the frequency with which the analyst forecasts the firm’s earnings, which Jacob et al. (1999) use to proxy the amount of effort the analyst devotes to following the company—is just as important as past forecast accuracy for explaining current forecast accuracy. The forecast model coefficients for past forecast accuracy and forecast frequency are 0.068 and 0.067, respectively, and the difference between them is statistically insignificant. Second, we find that forecast accuracy decreases with days elapsed since the last forecast—a new forecast characteristic not investigated in prior research. In sum, our results suggest that investors can use these characteristics of analysts and forecasts to predict forecast accuracy.

Tests of Association between Analysts’ Characteristics and Stock Returns

To investigate whether investors condition their responses to forecast revisions in a manner consistent with the analyst’s expected accuracy, we compare the coefficients from the forecast accuracy model (Equation [3]), which by construction has the same coefficients as the constrained returns model, with the corresponding coefficients from the unconstrained

---

13 A median standardized value of 0.5 would indicate that half of the firm-year observations are above the midpoint of the range for that variable. The medians in Table 1, Panel B show that for some variables, half of the observations are in the bottom 20 percent of the range of the variables. Our forecast accuracy regression model does not require the explanatory variables to conform to any particular distribution. However, our hypothesis tests assume that the distribution of the regression error term (i.e., the distribution of the dependent variable, forecast accuracy, conditional on the distribution of the explanatory variables) is normal.
TABLE 2  
Regression Model Coefficient Estimates for the Forecast Accuracy and Returns Models  
(all forecast revisions: n = 35,351)

\[
\begin{align*}
\text{ACCURACY}_{ijt} &= \alpha_0 + \alpha_1 \text{DAYS_ELAPSED}_{ijt} + \alpha_2 \text{FOR_HORIZON}_{ijt} \\
&+ \alpha_3 \text{LAG_ACCURACY}_{ijt} + \alpha_4 \text{BROKER_SIZE}_{ijt} \\
&+ \alpha_5 \text{FOR_FREQUENCY}_{ijt} + \alpha_6 \text{FIRM_EXPERIENCE}_{ijt} \\
&+ \alpha_7 \text{COMPANIES}_{ijt} + \alpha_8 \text{INDUSTRIES}_{ijt} + \varepsilon_{ijt} \quad (3)
\end{align*}
\]

\[
\begin{align*}
\text{CAR}_{ijt} &= \gamma_0 + \gamma_1 \text{REVP}_{ijt} \times (\alpha_0^* + \alpha_1^* \text{DAYS_ELAPSED}_{ijt} + \alpha_2^* \text{FOR_HORIZON}_{ijt} \\
&+ \alpha_3^* \text{LAG_ACCURACY}_{ijt} + \alpha_4^* \text{BROKER_SIZE}_{ijt} \\
&+ \alpha_5^* \text{FOR_FREQUENCY}_{ijt} + \alpha_6^* \text{FIRM_EXPERIENCE}_{ijt} \\
&+ \alpha_7^* \text{COMPANIES}_{ijt} + \alpha_8^* \text{INDUSTRIES}_{ijt}) + \varepsilon_{ijt} \quad (4)
\end{align*}
\]

**Panel A: Parameter Estimates**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Asymptotic Std. Error</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Asymptotic Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>$\alpha_1$</td>
<td>-0.032*** 0.0051</td>
<td>FOR_HORIZON</td>
<td>$\alpha_1^*$</td>
<td>0.236*** 0.0567</td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>$\alpha_2$</td>
<td>-0.229*** 0.0055</td>
<td>LAG_ACCURACY</td>
<td>$\alpha_2^*$</td>
<td>0.296*** 0.0604</td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>$\alpha_3$</td>
<td>0.068*** 0.0051</td>
<td>BROKER_SIZE</td>
<td>$\alpha_3^*$</td>
<td>0.101* 0.0571</td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>$\alpha_4$</td>
<td>0.024*** 0.0054</td>
<td>FOR_FREQUENCY</td>
<td>$\alpha_4^*$</td>
<td>0.391*** 0.0601</td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>$\alpha_5$</td>
<td>0.067*** 0.0055</td>
<td>FIRM_EXPERIENCE</td>
<td>$\alpha_5^*$</td>
<td>0.084 0.0627</td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>$\alpha_6$</td>
<td>0.020*** 0.0052</td>
<td>COMPANIES</td>
<td>$\alpha_6^*$</td>
<td>0.048 0.0575</td>
</tr>
<tr>
<td>COMPANIES</td>
<td>$\alpha_7$</td>
<td>-0.030*** 0.0066</td>
<td>INDUSTRIES</td>
<td>$\alpha_7^*$</td>
<td>-0.000 0.0728</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>$\alpha_8$</td>
<td>-0.019*** 0.0064</td>
<td>REVP</td>
<td>$\alpha_8^*$</td>
<td>-0.045 0.0711</td>
</tr>
<tr>
<td>REVP</td>
<td>$\gamma_1$</td>
<td>3.123*** 0.1230</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Panel B: Tests of Equality of Forecast and Returns Model Coefficients**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Likelihood Ratio Statistic</th>
<th>Marginal Significance Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>$\alpha_1 = \alpha_1^*$</td>
<td>8.53</td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>$\alpha_2 = \alpha_2^*$</td>
<td>21.77</td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>$\alpha_3 = \alpha_3^*$</td>
<td>1.02</td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>$\alpha_4 = \alpha_4^*$</td>
<td>18.93</td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>$\alpha_5 = \alpha_5^*$</td>
<td>0.81</td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>$\alpha_6 = \alpha_6^*$</td>
<td>0.66</td>
</tr>
<tr>
<td>COMPANIES</td>
<td>$\alpha_7 = \alpha_7^*$</td>
<td>1.86</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>$\alpha_8 = \alpha_8^*$</td>
<td>0.44</td>
</tr>
<tr>
<td>Overall (joint) test</td>
<td>$\alpha_i = \alpha_i^*$, $i = 1,...,8$</td>
<td>67.99</td>
</tr>
</tbody>
</table>

(continued on next page)
TABLE 2 (continued)

\* *, **Significantly different from zero at the 10, 5, and 1 percent levels, respectively.

\[ a \] We estimate \( \gamma_1 \) when we constrain the \( \alpha_i \) coefficient in Equation (4) to equal the corresponding \( \alpha_i \) coefficients from Equation (3).

\[
\begin{align*}
\text{CAR}_{ijt} (\text{cumulative abnormal return}) &= \text{three-trading-day cumulative market-adjusted abnormal return surrounding analyst } i \text{'s earnings forecast revision for firm } j \text{ in year } t. \text{ The accumulation period starts one day before the revision and ends one day after the revision. We compute the return by subtracting value-weighted market returns from firm } j \text{'s return; and} \\
\text{REVP}_{ijt} (\text{revision scaled by price}) &= \text{analyst } i \text{'s forecast revision for firm } j \text{ in year } t \text{ scaled by the end-of-day stock price two days prior to the revision. The revision equals analyst } i \text{'s forecast of firm } j \text{'s earnings in year } t \text{ less analyst } i \text{'s prior forecast of firm } j \text{'s earnings in year } t.
\end{align*}
\]

Other variables are defined in Table 1.

returns model (Equation [4]), also reported in Table 2, Panel A.\(^{14}\) If investors weight forecast revisions in accordance with rational expectations of forecast accuracy (as modeled in Equation [3]), then the coefficients for each of the characteristics should be the same in the forecast accuracy model and the unconstrained returns model (Equations [3] and [4], respectively).

All of the characteristics have significant coefficients in the forecast accuracy model, but only four characteristics have statistically significant coefficients in the unconstrained returns model: days elapsed, forecast horizon, past accuracy, and broker size. All four are positively associated with return responses to forecast revisions. Note, however, that both days elapsed and forecast horizon are associated with less accurate forecasts in the forecast accuracy model.

The remaining analyst characteristics are statistically insignificant in the unconstrained returns model, indicating that investors act as if they condition their responses to forecast revisions on only a subset of the characteristics that predict the revision’s accuracy. One explanation for this divergence between the forecast accuracy model and unconstrained returns model estimates is that investors believe that the cost of monitoring these analyst-specific details exceeds the benefit from improved estimates of forecast accuracy that monitoring may provide.\(^{15}\)

Panel B of Table 2 formally tests differences in coefficients estimated in the constrained and unconstrained returns models by comparing sums of squares for restricted and unrestricted returns models. After estimating the unrestricted model (which allows the returns model coefficients to differ from their forecast accuracy model counterparts), we then compute the restricted returns model by restricting the coefficient of each characteristic in turn to be equal in the forecast accuracy and stock returns models. We compute a Chi-square statistic based on the increase in residual sums of squares resulting from the restriction. The individual coefficients for days elapsed, forecast horizon, and broker size differ significantly in the two models at better than the 1 percent level. The positive coefficient for

\(^{14}\) We obtain similar coefficients and significance levels when we estimate the forecast accuracy and returns models using OLS. The R²’s for the forecast accuracy and returns models are 0.076 and 0.022, respectively, which are consistent with prior forecast accuracy research (e.g., Clement 1999; Mikhail et al. 1997).

\(^{15}\) Multicollinearity does not explain these variables' lack of significance in the stock returns model. We compute a Chi-square statistic to test the joint significance of the coefficients of forecast frequency, firm experience, and the number of companies and industries the analyst follows, in the stock returns model (\( \alpha_5 \) to \( \alpha_7 \)). The Chi-square statistic is 3.58, which is not statistically significant (4 degrees of freedom). In contrast, the corresponding variables in the forecast accuracy model are highly significant, both individually and jointly.
forecast horizon in the unconstrained returns model suggests that investors respond strongly
to timely forecasts, even though the forecast accuracy model reveals that those longer-
horizon forecasts are generally less accurate than later forecasts. Investors also respond
strongly to forecasts that break long absences of analyst forecasts for a given firm, even
though those forecasts are also less accurate than other forecasts. In addition, investors
appear to place more weight on broker size than seems warranted by the forecast accuracy
model’s coefficients, consistent with investors’ using analyst affiliation as a signal of fore-
cast accuracy. The differences in the coefficients on the remaining characteristics are sta-
tistically insignificant.

We also test the overall (joint) restriction of all coefficients by restricting all of the
characteristics’ coefficients to be equal in the forecast and unconstrained returns models.
This overall test shows that the forecast and returns model coefficients differ significantly
at better than the 1 percent level. We conclude that return responses to forecast revisions
are inconsistent with investors’ use of rational expectations of forecast accuracy (as modeled
in Equation [3]) to weight the revisions.16

Lagged forecast accuracy, a summary measure of forecast accuracy as documented in
Brown (2001), and broker size, which investors may use as a readily observable signal of
forecast accuracy (Hong and Kubik 2003) are the only characteristics that are significantly
associated with both forecast accuracy and stock returns in a consistent manner (i.e., with
increased forecast accuracy and increased return responses). We therefore investigate
whether the relative importance of these two key analyst characteristics differs in the fore-
cast accuracy and unconstrained returns models. In the forecast accuracy model, the lagged
forecast accuracy coefficient is significantly higher than the broker-size coefficient, but in
the returns model, the lagged forecast accuracy coefficient is significantly lower than the
broker-size coefficient (both at better than the 1 percent significance level).17 These results
reinforce our conclusion that investors do not respond solely to prior or predicted forecast
accuracy. Furthermore, investors appear to respond more strongly to an easily observable
analyst characteristic (broker size) than to a less easily observed characteristic (lagged
forecast accuracy), even though lagged forecast accuracy is more strongly associated with
forecast accuracy. This result suggests that investors use broker size as a summary indicator
of analyst accuracy, and is consistent with Hong and Kubik’s (2003) conclusion that large
brokerage firms tend to hire and retain accurate forecasters.

In summary, the results in Table 2 suggest that forecast frequency, firm experience, and
the number of companies and industries the analyst follows are significantly associated with
forecast accuracy but not with returns. Although lagged forecast accuracy is more important
than broker size in explaining forecast accuracy, it is less important than broker size in
explaining the magnitude of the price reactions to forecast revisions. More surprisingly,
forecast horizon and days elapsed since the last forecast are both associated with less
accurate forecasts, but with larger price reactions to forecast revisions. Collectively, these

16 We base this conclusion on the overall test in Panel B of Table 2, which shows that the forecast and returns
model coefficients are significantly different. Although some individual characteristics (such as past accuracy,
forecast frequency, and firm experience) have statistically similar coefficients in the forecast accuracy and returns
models, the results in Panel A show that forecast frequency, firm experience, and companies and industries
followed are not significantly associated with returns, indicating that investors respond to just a subset of the
characteristics that are associated with forecast accuracy. Predictions of forecast accuracy that are based on only
a subset of informative analyst characteristics are inconsistent with rational expectations because they ignore
relevant information.

17 We can compare the coefficient estimates because we scale both variables to range from 0 to 1. The coefficient
for each scaled variable measures the return response to forecast revisions when that variable is at its highest
level within a firm-year (i.e., when the scaled explanatory variable is 1).
results support our conclusion that investor responses to analysts’ forecast revisions reflect characteristics other than predicted forecast accuracy. Specifically, investors respond strongly to timely forecasts and appear to use broker size as a proxy for forecast accuracy.

**Sensitivity Analysis**

We perform several sensitivity analyses to check the robustness of the results. First, we examine whether controlling for (a proxy for) the level of prior uncertainty affects our inferences. Second, we partition the sample into high-innovation and low-innovation forecasts, as defined by Gleason and Lee (2003), to determine whether this partition drives our findings that returns respond more strongly to timely forecast revisions and revisions by analysts employed by large brokers. Finally, we estimate single-characteristic regressions as an additional test for possible effects of multicollinearity in the stock returns model. As explained below, our primary inferences remain unchanged after performing these tests.

Theory predicts that investor responses to forecast revisions increase with both the precision of the forecast and the precision of investors’ prior information (Kim and Verrecchia 1991; Abarbanell et al. 1995). Our returns model focuses on the role of predicted forecast precision. To ensure that our results are not attributable to the omission of the precision of investors’ prior information, or prior uncertainty, we reestimate the returns model after including a proxy for prior uncertainty. Following Barron et al.’s (1998) theoretical analysis of financial analysts’ information environment, we measure prior uncertainty as the mean squared forecast error of all prior forecasts outstanding at each forecast date. Our uncertainty proxy measures the overall error among analysts, but is based on actual earnings information that is not available at the time of the forecast.18 Similar to our other explanatory variables, we standardize prior uncertainty to range from 0 to 1 for each firm-year. We estimate the following model:

\[
\text{CAR}_{ijt} = \gamma_0 + \gamma_1 \text{REVP}_{ijt} \times (\alpha_{ij}^\text{DAYS_ELAPSED} + \alpha_{ij}^\text{FOR_HORIZON}) + \alpha_{ij}^\text{LAG_ACCURACY} \times \text{LAG ACCURACY}_{ijt} + \alpha_{ij}^\text{BROKER_SIZE} \times \text{BROKER SIZE}_{ijt} + \alpha_{ij}^\text{FOR_FREQUENCY} \times \text{FOR FREQUENCY}_{ijt} + \alpha_{ij}^\text{FIRM_EXPERIENCE} \times \text{FIRM EXPERIENCE}_{ijt} + \alpha_{ij}^\text{COMPANIES} \times \text{COMPANIES}_{ijt} + \alpha_{ij}^\text{INDUSTRIES} \times \text{INDUSTRIES}_{ijt}) + \gamma_2 \text{REVP}_{ijt} \times \text{UNCERTAINTY}_{ijt} + \epsilon_{ijt},
\]

where:

\[
\text{UNCERTAINTY}_{ijt} = \frac{\text{mean squared forecast error of analyst forecasts immediately prior to analyst } i \text{'s forecast revision for firm } j \text{ in year } t, \text{ minus the minimum mean squared forecast error of forecasts immediately preceding the forecast revisions of analysts following firm } j \text{ in year } t,\text{ all scaled by the range of mean squared forecast errors preceding forecasts of analysts following firm } j \text{ in year } t.}
\]

We use the same prediction model for forecast accuracy as in the previous analysis.

---

18 Barron et al. (1998, 424) label their uncertainty measure \( V \), and define it as the expected squared forecast error from the earnings random variable. We use realized forecast errors because of the practical difficulty of measuring expected forecast errors for successive analyst forecasts. A possible alternative is to estimate uncertainty at a given date as the squared forecast error for forecasts outstanding on the same date in a preceding year. The disadvantage of that approach is that analysts’ uncertainty may change from year to year with the firm’s economic conditions.
However, the modified returns model in Equation (5) includes a response to predicted forecast accuracy, or forecast precision (measured with $\gamma_1$) and a response to prior uncertainty (measured with $\gamma_2$). In unreported results, we find that the coefficient on prior uncertainty ($\gamma_2$) is significantly positive. Interestingly, the forecast horizon coefficient is insignificant when we include prior uncertainty in the model. Therefore, return responses to forecast revisions (1) increase with prior uncertainty, and (2) are not significantly associated with forecast horizon when we include prior uncertainty in the model. The coefficients on our other variables are essentially unchanged in this model, and our primary inferences are unaltered. Specifically, investor responses to forecast revisions are inconsistent with the use of analyst and forecast characteristics to derive rational expectations of analyst forecast accuracy.

In our second sensitivity test we partition the sample in a manner similar to Gleason and Lee (2003). They find that high-innovation forecast revisions (new forecasts that are above both the analysts’ prior forecast and the consensus forecast, or else are below both forecasts) have a greater price effect than low-innovation forecasts. This finding could explain our results if analyst characteristics such as forecast horizon and broker size are correlated with innovation. Thus, we estimate separately the forecast accuracy and stock returns models for high-innovation and low-innovation forecasts. We report the results in Tables 3 and 4, respectively.

Table 3, Panel A shows that the results for high-innovation forecasts are similar to the results for the full sample. Specifically, forecast frequency, firm experience, and the number of companies and industries the analyst follows are significantly associated with forecast accuracy but not with returns. Days elapsed since the prior forecast and forecast horizon are both associated with less accurate forecasts, but with larger price reactions to forecast revisions. Broker size is significantly associated with greater forecast accuracy and with larger price reactions to forecast revisions. This is the only analyst characteristic whose association with forecast accuracy is consistent with its association with returns. The results in Table 3, Panel B are also similar to the full sample results. The overall test shows that the coefficient estimates for analyst characteristics are significantly different in the forecast accuracy and returns models. The estimated coefficients for days elapsed, forecast horizon, broker size, and the number of companies followed are all significantly different in the forecast accuracy and returns models. Thus even among high-innovation forecasts, analyst characteristics still contribute significantly to explaining return responses, but return responses to analyst forecast revisions are inconsistent with rational expectations of forecast accuracy.

Table 4 shows that for low-innovation forecasts, the results for the forecast accuracy model are similar to the full sample results and to the results for high-innovation forecasts in Table 3. However, in the unconstrained stock returns model, only the forecast frequency coefficient is statistically significant (at the 10 percent level). More importantly, a test of the joint significance of all the analyst characteristics in the unconstrained returns model

19 The simple correlation between prior uncertainty and forecast horizon is 0.66, indicating that longer forecast horizons are strongly associated with more prior uncertainty among analysts.

20 We repeated the analysis including prior uncertainty in both the forecast accuracy model and the returns model. We find that prior uncertainty and forecast horizon are both associated with reduced forecast accuracy in the forecast accuracy model. In the returns model, prior uncertainty is strongly associated with increased return responses to forecast revisions, but forecast horizon is associated with reduced return responses to forecast revisions, consistent with the forecast accuracy model. Tests of the forecast and returns model coefficients show that these results are still inconsistent with investors’ use of rational expectations of forecast accuracy in responding to analyst forecast revisions.
TABLE 3
Regression Model Coefficient Estimates for the Forecast Accuracy and Returns Models
(high-innovation forecast revisions: n = 25,445)

\[
\text{ACCURACY}_{ijt} = \alpha_0 + \alpha_1 \text{DAYS}_\text{ELAPSED}_{ijt} + \alpha_2 \text{FOR}_\text{HORIZON}_{ijt} \\
+ \alpha_3 \text{LAG}_\text{ACCURACY}_{ijt} + \alpha_4 \text{BROKER}_\text{SIZE}_{ijt} \\
+ \alpha_5 \text{FOR}_\text{FREQUENCY}_{ijt} + \alpha_6 \text{FIRM}_\text{EXPERIENCE}_{ijt} \\
+ \alpha_7 \text{COMPANIES}_{ijt} + \alpha_8 \text{INDUSTRIES}_{ijt} + \epsilon_{ijt} 
\]

\[
\text{CAR}_{ijt} = \gamma_0 + \gamma_1 \text{REVP}_{ijt} \times (\alpha_0 + \alpha_1 \text{DAYS}_\text{ELAPSED}_{ijt} + \alpha_2 \text{FOR}_\text{HORIZON}_{ijt} \\
+ \alpha_3 \text{LAG}_\text{ACCURACY}_{ijt} + \alpha_4 \text{BROKER}_\text{SIZE}_{ijt} \\
+ \alpha_5 \text{FOR}_\text{FREQUENCY}_{ijt} + \alpha_6 \text{FIRM}_\text{EXPERIENCE}_{ijt} \\
+ \alpha_7 \text{COMPANIES}_{ijt} + \alpha_8 \text{INDUSTRIES}_{ijt}) + \epsilon_{ijt} 
\]

Panel A: Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Asymptotic Std. Error</th>
<th>Estimate</th>
<th>Asymptotic Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>$\alpha_1$</td>
<td>-0.036***  0.0061</td>
<td>$\alpha_1^*$</td>
<td>0.287***  0.0567</td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>$\alpha_2$</td>
<td>-0.238***  0.0066</td>
<td>$\alpha_2^*$</td>
<td>0.292***  0.0608</td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>$\alpha_3$</td>
<td>0.067***  0.0062</td>
<td>$\alpha_3^*$</td>
<td>0.087     0.0577</td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>$\alpha_4$</td>
<td>0.027***  0.0065</td>
<td>$\alpha_4^*$</td>
<td>0.374***  0.0605</td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>$\alpha_5$</td>
<td>0.056***  0.0066</td>
<td>$\alpha_5^*$</td>
<td>-0.015   0.0627</td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>$\alpha_6$</td>
<td>0.016***  0.0063</td>
<td>$\alpha_6^*$</td>
<td>0.014     0.0578</td>
</tr>
<tr>
<td>COMPANIES</td>
<td>$\alpha_7$</td>
<td>-0.032***  0.0079</td>
<td>$\alpha_7^*$</td>
<td>0.012     0.0737</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>$\alpha_8$</td>
<td>-0.017**   0.0078</td>
<td>$\alpha_8^*$</td>
<td>-0.019   0.0719</td>
</tr>
<tr>
<td>REVP$^b$</td>
<td></td>
<td></td>
<td>$\gamma_1$</td>
<td>3.557***  0.1360</td>
</tr>
</tbody>
</table>

Panel B: Tests of Equality of Forecast and Returns Model Coefficients

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Likelihood Ratio Statistic</th>
<th>Marginal Significance Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>$\alpha_1 = \alpha_1^*$</td>
<td>12.73</td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>$\alpha_2 = \alpha_2^*$</td>
<td>23.29</td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>$\alpha_3 = \alpha_3^*$</td>
<td>0.67</td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>$\alpha_4 = \alpha_4^*$</td>
<td>18.83</td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>$\alpha_5 = \alpha_5^*$</td>
<td>1.23</td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>$\alpha_6 = \alpha_6^*$</td>
<td>0.65</td>
</tr>
<tr>
<td>COMPANIES</td>
<td>$\alpha_7 = \alpha_7^*$</td>
<td>3.92</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>$\alpha_8 = \alpha_8^*$</td>
<td>0.57</td>
</tr>
<tr>
<td>Overall (joint) test</td>
<td>$\alpha_i = \alpha_i^*$, i = 1,...,8</td>
<td>75.43</td>
</tr>
</tbody>
</table>

*, **, *** Significantly different from zero at the 10, 5, and 1 percent levels, respectively.

a High-innovation forecast revisions are above both the analyst’s own prior forecast and the consensus forecast, or else are below both forecast revisions.

b We estimate $\gamma_1$ when we constrain the $\alpha_i^*$ coefficients in Equation (4) to equal the corresponding $\alpha_i$ coefficients from Equation (3).

Variables are defined in Tables 1 and 2.
TABLE 4
Regression Model Coefficient Estimates for the Forecast Accuracy and Returns Models
(low-innovation forecast revisions:* n = 10,086)

\[
\text{ACCURACY}_{ijt} = \alpha_0 + \alpha_1 \text{DAYS ELAPSED}_{ijt} + \alpha_2 \text{FOR HORIZON}_{ijt}
+ \alpha_3 \text{LAG ACCURACY}_{ijt} + \alpha_4 \text{BROKER SIZE}_{ijt}
+ \alpha_5 \text{FOR FREQUENCY}_{ijt} + \alpha_6 \text{FIRM EXPERIENCE}_{ijt}
+ \alpha_7 \text{COMPANIES}_{ijt} + \alpha_8 \text{INDUSTRIES}_{ijt} + \varepsilon_{ijt}
\]  

\[
\text{CAR}_{ijt} = \gamma_0 + \gamma_1 \text{REVP}_{ijt} \times (\alpha_0^* + \alpha_1^* \text{DAYS ELAPSED}_{ijt} + \alpha_2^* \text{FOR HORIZON}_{ijt}
+ \alpha_3^* \text{LAG ACCURACY}_{ijt} + \alpha_4^* \text{BROKER SIZE}_{ijt}
+ \alpha_5^* \text{FOR FREQUENCY}_{ijt} + \alpha_6^* \text{FIRM EXPERIENCE}_{ijt}
+ \alpha_7^* \text{COMPANIES}_{ijt} + \alpha_8^* \text{INDUSTRIES}_{ijt}) + \varepsilon_{ijt}
\]  

Panel A: Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Asymptotic Std. Error</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Asymptotic Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>$\alpha_1$</td>
<td>$-0.021^{**}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>$\alpha_2$</td>
<td>$-0.221^{***}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>$\alpha_3$</td>
<td>$0.064^{***}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>$\alpha_4$</td>
<td>$0.007$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>$\alpha_5$</td>
<td>$0.077^{***}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>$\alpha_6$</td>
<td>$0.024^{***}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COMPANIES</td>
<td>$\alpha_7$</td>
<td>$-0.024^{**}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>$\alpha_8$</td>
<td>$-0.016$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>REVP$^b$</td>
<td>$\gamma_1$</td>
<td>$1.080^{***}$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Tests of Equality of Forecast and Returns Model Coefficients

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Likelihood Ratio Statistic</th>
<th>Marginal Significance Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAYS_ELAPSED</td>
<td>$\alpha_1 = \alpha_1^*$</td>
<td>1.61</td>
</tr>
<tr>
<td>FOR_HORIZON</td>
<td>$\alpha_2 = \alpha_2^*$</td>
<td>2.78</td>
</tr>
<tr>
<td>LAG_ACCURACY</td>
<td>$\alpha_3 = \alpha_3^*$</td>
<td>0.08</td>
</tr>
<tr>
<td>BROKER_SIZE</td>
<td>$\alpha_4 = \alpha_4^*$</td>
<td>2.43</td>
</tr>
<tr>
<td>FOR_FREQUENCY</td>
<td>$\alpha_5 = \alpha_5^*$</td>
<td>2.19</td>
</tr>
<tr>
<td>FIRM_EXPERIENCE</td>
<td>$\alpha_6 = \alpha_6^*$</td>
<td>0.77</td>
</tr>
<tr>
<td>COMPANIES</td>
<td>$\alpha_7 = \alpha_7^*$</td>
<td>0.73</td>
</tr>
<tr>
<td>INDUSTRIES</td>
<td>$\alpha_8 = \alpha_8^*$</td>
<td>0.18</td>
</tr>
<tr>
<td>Overall (joint) test</td>
<td>$\alpha_i = \alpha_i^*$, i = 1,...,8</td>
<td>2.57</td>
</tr>
</tbody>
</table>

* ** *** Significantly different from zero at the 10, 5, and 1 percent levels, respectively.

*a Low-innovation forecasts are forecasts that are above the analyst's prior forecast but below the consensus forecast, or vice versa.

b We estimate $\gamma_1$ when we constrain the $\alpha_i^*$ coefficient in Equation (4) to equal the corresponding $\alpha_i$ coefficients from Equation (3).

Variables are defined in Tables 1 and 2.
shows that the characteristics’ coefficients are not statistically significant (results not reported). Because investors appear to ignore analyst characteristics that the forecast accuracy model shows are predictive of forecast accuracy when those investors respond to low-innovation forecast revisions, we cannot reach a definitive conclusion on the rationality of investors’ (non) response to analyst characteristics for low-innovation forecasts, even though Panel B of Table 4 shows that there are no significant differences between the constrained and unconstrained returns model coefficients. We note, however, that the forecast accuracy model suggests that analyst and forecast characteristics are informative about the accuracy of both low-innovation and high-innovation forecasts, so Gleason and Lee’s (2003) results are not attributable to differences in the information that analyst characteristics provide about the accuracy of low-innovation vs. high-innovation forecasts. Thus, it seems inconsistent for investors to respond to analyst characteristics for high-innovation forecasts but not for low-innovation forecasts.

Our findings extend Gleason and Lee’s (2003) results by demonstrating that additional factors beyond revision innovation affect the magnitude of price reactions to high-innovation forecasts. Our analysis also extends their work by providing evidence that investors respond to high-innovation forecast revisions as if accuracy is not all that matters. Furthermore, even though the accuracy of high-innovation and low-innovation forecasts is similarly associated with analyst characteristics such as days elapsed since the last forecast, forecast horizon, past accuracy, and broker size, return reactions to forecast revisions differ substantially for the two types of forecasts. The reactions to high-innovation forecasts are more closely associated with analyst and forecast characteristics than are the reactions to low-innovation forecasts. In sum, our overall conclusion is that investor response to high-innovation forecast revisions is inconsistent with the use of rational expectations of forecast accuracy to weight forecast revisions.

Finally, to ensure that our inferences are not attributable to multicollinearity in the stock returns model, we estimate single-characteristic regressions by regressing the cumulative abnormal returns on the revision and on the revision interacted with each individual characteristic. The coefficient magnitudes, signs, and significance levels are similar to the estimates from the multiple regressions. Specifically, the coefficients of forecast frequency, firm experience, and number of companies and industries followed are statistically insignificant, whereas the coefficients of days elapsed since the prior forecast, forecast horizon, lagged accuracy, and broker size are statistically significant. Therefore, our conclusions about the significance of individual return model coefficients are not likely due to multicollinearity.

V. CONCLUSION

We investigate two related issues. First, we examine whether investors respond to all of the information that a comprehensive set of analyst characteristics provides about forecast accuracy. Second, we examine whether factors other than forecast accuracy, such as forecast timeliness and broker size, have incremental value-relevance after controlling for predicted accuracy.

Our results suggest that investors respond to a subset of analyst characteristics that are associated with forecast accuracy, suggesting that investors form earnings expectations using more complex procedures than simply averaging all analysts’ forecasts. Holding the magnitude of the revision constant, we find that investor response increases with both broker

---

21 Intuitively, the confidence intervals for the analyst characteristic coefficients in the unconstrained returns model include both zero (Panel A) and the forecast model estimates (Panel B).
size and the analyst’s prior forecast accuracy. Although both our study and Brown (2001) find that past forecast accuracy is more important than broker size for predicting current forecast accuracy, we find that broker size is more important than past forecast accuracy for explaining stock returns around forecast revisions. This result is consistent with investors’ reliance on analyst affiliation as a summary indicator of forecast accuracy. Our results also leave open the possibility that different types of investors weight analyst characteristics differently when responding to forecast revisions. Bonner et al. (2002) find that sophisticated investors respond to forecast revisions as if they have better knowledge of the association between analyst characteristics and forecast accuracy than do unsophisticated investors. These differences in response could occur if the costs and benefits of monitoring analyst characteristics differ by investor type.

In addition, our results suggest that investors’ responses to forecast revisions are influenced by characteristics other than forecast accuracy. For example, although forecasts with longer forecast horizons tend to be less accurate than forecasts with shorter horizons, investors respond more strongly to the earlier forecasts than to the later forecasts. Forecast horizon is significantly associated with the level of uncertainty about earnings, and the strong return response to timely forecasts appears to be due to the greater level of uncertainty about earnings early in the year. Similarly, return responses to forecast revisions increase with days elapsed since the prior forecast even though those forecasts are less accurate. This suggests that there is a trade-off between accuracy vs. timeliness and time elapsed since the prior forecast in the usefulness of forecasts to investors.

In closing, we offer three caveats. First, returns are associated with analyst characteristics only in the subset of the forecasts that either exceed both the analyst’s prior forecast and the consensus forecast, or are below both the analyst’s prior forecast and the consensus forecast—that is, for high-innovation forecasts (Gleason and Lee 2003). We find insignificant association between returns and analyst characteristics for the remaining (low-innovation) forecasts.

Second, our returns model assumes that expected forecast accuracy is the primary determinant of return responses to forecast revisions. Our goal is to test this maintained hypothesis against the alternate hypothesis that investors respond to characteristics in a manner that is inconsistent with rational reliance on expected forecast accuracy alone. Our results suggest that another forecast attribute—timeliness—is important to investors, and other (unidentified) value-relevant analyst or forecast characteristics could be omitted from our models.

The third caveat is that we standardize each firm’s forecast accuracy to lie between 0 and 1, and we assume a linear forecast accuracy model. Although investors might respond nonlinearly to analyst characteristics that predict forecast accuracy, this possibility cannot explain our results. Days elapsed since the last forecast and forecast timeliness are both associated with reduced forecast accuracy, but with increased return responses. Our standardization preserves the rank order of the observations, and variables that are associated with less accurate forecasts should still be associated with smaller return responses after standardization. Our results suggest that return responses to analysts’ forecast revisions are associated with analyst and forecast characteristics, but in a manner that is inconsistent with investors responding to expected forecast accuracy alone.

REFERENCES


