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Kim, Yongtae, Gerald J. Lobo, and Minsup Song. "Analyst Characteristics, Timing of Forecast Revisions, and Analyst Forecasting Ability." Journal of Banking & Finance 35.8 (2011): 2158-168.

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Working Paper Yongtae Kim Associate Professor of Accounting Santa Clara University WP# 11-04

Analyst Characteristics, Timing of Forecast Revisions, and Analyst Forecasting Ability

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Abstract

We first examine whether analysts with certain characteristics that prior research has identified are related to superior forecasting ability systematically time their forecast revisions later in the fiscal quarter. We then examine whether this superior ability persists after controlling for this timing advantage by using relative forecast error, a measure that largely eliminates the timing advantage of recent forecasts. Using a sample of quarterly earnings forecast revisions over the 20-year period from 1990 to 2009, we find that analysts with more firm-specific and general experience and more accurate prior-period forecasts, analysts employed by larger brokerage firms, and analysts who follow fewer industries and companies tend to revise forecasts later in the quarter. We also find that analyst characteristics that are positively correlated with revision timing are negatively related to relative forecast errors. These results are consistent with analyst characteristics being useful proxies for analyst forecasting ability and analysts with greater ability revising forecasts later in the quarter.

JEL classification: G24; M41; D82

Keywords: Analyst earnings forecasts; Forecast revisions; Analyst characteristics; Forecast timing; Forecasting ability

We are grateful to workshop participants at the 2009 American Accounting Association annual meeting, 2009 Financial Management Association annual meeting, 2009 European Financial Management Association meeting, and Korea University for helpful comments and suggestions. Kim acknowledges financial support provided by the Leavey Research Grant and a Breetwor Fellowship.

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1. Introduction

Prior research indicates that forecast accuracy is associated with analyst characteristics (Clement et al., 2003; Clement, 1999; Jacob et al., 1999; Mikhail et al., 1997). Clement (1999) and Clement and Tse (2003), for example, document that forecast accuracy increases with firmspecific and general experience, prior forecast accuracy, and affiliation with a larger brokerage firm, and decreases with the number of firms and industries followed, suggesting that these analyst characteristics can serve as proxies for analyst forecasting ability. It is also wellestablished that more recent analyst forecasts are more accurate than forecasts issued earlier in the period (e.g., O'Brien, 1988). This superiority of forecasts issued later in the period can be attributed, in part, to the timing advantage of recent forecasts (Brown, 1993). That is, by delaying their forecasts, analysts can observe other analysts' forecasts issued earlier, as well as other firm disclosures, so that they can utilize more information as the earnings-announcement date draws near. It is unclear from prior work whether the observed relation between analyst characteristics and forecast accuracy is primarily attributable to the variation in analyst forecasting ability or to the timing advantage of more recent forecasts. In other words, the timing of analyst forecasts could explain the observed relation between analyst characteristics and forecast accuracy documented by prior research.

In this study, we first investigate whether analyst characteristics are associated with the timing of forecast revisions. After documenting that the timing of our sample forecast revisions is associated with analyst characteristics, we then examine the relation between analyst characteristics and relative forecast error. This forecast error measure eliminates the timing advantage of recent forecasts by subtracting the most recent consensus analyst forecast error from the individual analyst forecast error (Ivković and Jegadeesh, 2004). Relative forecast error,

therefore, represents the revised forecast's accuracy relative to the accuracy of the existing consensus forecast which, in turn, reflects the existing set of information. A statistically significant relation between relative forecast error and analyst characteristics would provide more direct evidence that analyst characteristics examined in prior studies truly represent analyst forecasting ability. Together with the relation between analyst characteristics and the timing of forecast revisions, this evidence in turn would suggest that analysts with characteristics correlated with analysts' presumed ability forecast later or earlier in the fiscal period.

Although the literature on analyst forecasts in such areas as accuracy and other statistical properties of forecasts, informativeness of forecasts, and analyst economic incentives is abundant, very little attention is given to the timing of analyst forecasts and factors associated with this timing. Guttman (2010) is an important exception. He develops an analytical model that endogenizes the timing decision of analysts and examines their equilibrium timing strategies. This model predicts that analysts with higher precision of initial private information tend to forecast earlier, and analysts with higher learning ability tend to forecast later. To the best of our knowledge, no empirical research examines the dynamics of the forecast timing decision or considers analyst characteristics as potential determinants of forecast timing.

Stickel (1989) shows that security analysts tend to avoid revising forecasts for two weeks before an interim earnings announcement and revise immediately after the announcement. However, he does not examine the determinants of this timing. Other studies examine the timing of forecasts and analyst performance. For example, Cooper et al. (2001) report that lead analysts, identified by their measure of forecast timeliness, have a greater impact on stock prices than follower analysts. Ivković and Jegadeesh (2004) document that the relative precision of and market reaction to analyst forecasts are smaller immediately after the prior-period earnings

announcement, but larger before the current period earnings announcement. Although these two studies examine the association between the timing of analyst forecasts and their accuracy and price impact, analyst characteristics likely affect forecast timing as well as accuracy and price impact. Focusing on analyst forecasts immediately following an earnings announcement and post-earnings-announcement drift, Zhang (2008) finds that more responsive analyst forecasts (i.e., forecasts issued within two days following the earnings announcement) reduce post-earnings-announcement drift. O'Brien, et al. (1988) provide limited evidence on the relation between analyst characteristics and timeliness of recommendations. They find that analyst investment banking affiliations influence timeliness in downgrading recommendations.

Forecast timing is an important decision for sell-side analysts. On the one hand, a timely forecast can benefit a brokerage firm by triggering greater trading and increased commissions, which ultimately benefit analysts (e.g., Cooper et al., 2001; Irvine, 2003; Jackson, 2005). On the other hand, a timely forecast may sacrifice forecast accuracy by reducing opportunities for the analyst to observe other analysts' forecasts and their private information, as well as other information that becomes available as the fiscal period progresses. Analysts are concerned about less accurate forecasts because forecast accuracy is an important determinant of analyst career success (Hong and Kubik, 2003; Hong et al., 2000; Stickel, 1989). Frequent forecast revisions cannot solve this trade-off problem between timeliness and accuracy of analyst forecasts, because frequent forecast revisions could harm an analyst's reputation by sending market participants a negative signal that the analyst's prior information is less accurate (Trueman, 1990). As a result, analysts consider costs and benefits when deciding the timing of their forecasts.

In this study, we examine individual analyst decisions to time their forecast revisions during the fiscal quarter and the implications of various analyst characteristics for forecast revision timing. Using a sample of forecast revisions over the 20-year period from 1990 to 2009, we find that analyst characteristics are significantly related to the timing of analyst forecast revisions. Specifically, we find that analysts with more firm-specific and general experience and more accurate prior-period forecasts, analysts employed by larger brokerage firms, and analysts who follow fewer industries and companies tend to revise forecasts later in the quarter. We also find that analyst characteristics that are positively correlated with revision timing are negatively associated with relative forecast errors. These results are consistent with analyst characteristics being useful proxies for analyst forecasting ability and analysts with greater ability revising forecasts later in the quarter.

Our study contributes to prior literature in several ways. First, our empirical results yield insights into the forecasting behavior of sell-side analysts by showing that analyst forecast timing is endogenously determined. Prior empirical studies implicitly assume that the timing of analyst forecasts is determined exogenously. However, Chen (2007) and Guttman (2010) suggest that analysts strategically decide their forecast timing and consider costs and benefits when doing so. Chen (2007) provides one explanation for why analysts with greater forecast accuracy may time their forecast revisions later in the fiscal period. In a model in which analysts strategically time their forecasts to convince the public that they are skilled, he demonstrates that it is optimal for analysts with higher ex-ante reputation to delay their forecasts. Chen (2007) argues that this result indicates that analysts who already enjoy a favorable market assessment will not want to "go out on a limb" if there is little to be gained by forecasting early. Consistent with Chen's

(2007) model predictions, we find that analysts with greater forecasting ability, who likely have higher ex-ante reputation, delay their forecasts.

Guttman (2010) studies analyst equilibrium forecast timing strategies and illustrates that the equilibrium has one of two patterns: either the times of the analyst forecasts cluster, or there is a separation in the times of the forecasts. Clustering is likely when analysts are sufficiently alike, whereas separation is likely when analysts are sufficiently different. Guttman (2010) also demonstrates that analysts with higher precision of initial private information tend to forecast earlier, whereas analysts with higher learning ability tend to forecast later. Our empirical evidence is consistent with the predictions of Guttman (2010) if analysts are endowed with initial private information of similar precision and analyst characteristics are correlated with learning ability.

Second, given that analyst forecasts are used as a proxy for investor expectations of earnings in accounting and finance research, it is important to know whether there exist non-trivial differences in properties of forecasts and forecast revisions issued at different times during the fiscal period, and which factors contribute to the timing of forecasts and forecast revisions. Schipper (1991) calls for research on incentives analysts face when forming forecasts and how those incentives affect properties of analyst forecasts. In particular, she points out the potential tradeoff between timeliness and accuracy that affects analyst forecasting decisions; however, research on this issue is limited. Our study provides insights into how analyst characteristics affect this tradeoff between timeliness and accuracy. In addition, we show that the temporal trend of forecast accuracy is attributable not only to the timing advantage of recent forecasts, but also to analysts with superior forecasting ability revising their forecasts later in the quarter.

Our study also has implications for investors who could benefit from understanding the relation between analyst characteristics and forecast accuracy. This knowledge would help them select which analyst forecast to rely on when faced with multiple forecasts from different analysts. The association between forecast accuracy and analyst characteristics documented in prior research may reflect the timing advantage of forecasts made later in the period, and that analysts with different characteristics forecast at different times during the fiscal period. If so, the association between analyst characteristics and forecasting ability documented in prior research may be distorted. We show that analyst characteristics reflect true forecasting ability of analysts as reflected in relative forecast error. Investors could also benefit from understanding the association between forecast timing, analyst characteristics, and relative forecast accuracy, as this knowledge would allow them to more clearly isolate analyst superior ability from forecast timing.

Finally, forecast timing is an important decision for sell-side analysts as investor payoffs for analyst services depend on the timing of forecasts (Guttman, 2010). Therefore, understanding the dynamics of forecast revision timing would help analysts in formulating their forecast timing strategy when competing with other analysts.

The remainder of the paper is organized as follows. We discuss the sample and measures of analyst characteristics in Section 2. Sections 3 through 5 present the empirical results, and the final section summarizes our conclusions.

2. Sample and measures of analyst characteristics

2.1. Sample selection

We obtain data on sell-side analyst forecasts of earnings per share (EPS) for the period between January 1990 and December 2009 from the Institutional Brokers' Estimate System (I/B/E/S) detail tape. We focus on quarterly EPS forecasts that were revised after the priorquarter (q-1) earnings announcement date. We focus on quarterly forecasts because analysts more frequently revise their forecasts for annual earnings and, therefore, the timing of forecast revisions is a less critical decision for annual earnings than for quarterly earnings. We obtain earnings announcement dates from the COMPUSTAT quarterly files and stock return data from the Center for Research in Security Prices (CRSP) database. We require analysts to follow the firm for at least one quarter prior to the current quarter so that we can calculate analyst forecast accuracy in the prior quarter. We also require at least two analysts to follow the firm on the day before the forecast revision so that we can determine a consensus forecast prior to the revision. These criteria yield a sample of 402,879 quarterly earnings forecast revisions, of which 168,545 are upward revisions and 234,334 are downward revisions. The larger frequency of downward revisions than upward revisions is consistent with analyst optimistic bias documented in prior research (Ivković and Jegadeesh, 2004; Klein, 1990; O'Brien, 1988). We retain the first revision for each analyst, leaving 332,273 quarterly forecast revisions, of which 136,633 are upward revisions and 196,640 are downward revisions.² We choose the first forecast revision to avoid econometric problems stemming from including multiple revisions by the same analyst in the sample. In addition, the timing of forecast revision is the more critical decision for the first

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¹ When an analyst releases the first forecast prior to the q-l earnings announcement and revises the forecast later, we include only revisions issued after the q-l announcement in the sample. When an analyst issues the first forecast after the q-l announcement and revises later, we include only the revision (the second forecast) in our sample.

² We repeat our analyses on a sample that includes all forecast revisions as well as a sample of last revisions and report the results later in the paper. Our results are robust to these alternatives.

revision. Furthermore, this sample choice also enables us to compare our results with those in Ivković and Jegadeesh (2004). After we eliminate forecast revisions with missing data on firm characteristics, we have a final sample of 242,701 quarterly forecast revisions, of which 100,962 are upward revisions and 141,739 are downward revisions.

2.2. Analyst characteristics

We use a set of analyst characteristics that prior research has identified as proxies for analyst self-assessed ability. These include analyst experience, resources available to analysts, and complexity of portfolio covered by analysts, which are positively correlated with the variables that predict forecast accuracy (Clement, 1999; Clement and Tse, 2003; Clement and Tse, 2005; Jacob et al., 1999; Mikhail et al., 1997). Following previous studies, we use analyst characteristics including $FirmEXP_{ijq}$ which represents analyst i's firm-specific experience (measured as the number of quarters of firm-specific experience for analyst i following the firm j in quarter q), $GenEXP_{ijq}$ which represents analyst i's career experience (measured as the number of quarters of career experience for analyst i following the firm j in quarter q), $Industries_{ijq}$ which is the number of industries analyst i follows during the year (measured as the number of I/B/E/S industries followed during the year by analyst i following the firm j in quarter q), Prior Accuracy $_{ijq}$ which represents analyst i's prior period forecast accuracy (measured as the absolute forecast error for quarter q-1 EPS by analyst i following the firm j in quarter q), $Broker_Size_{ijq}$ which represents the analyst's brokerage firm size (measured as the number of analysts employed during the year by the brokerage firm employing analyst i following the firm j in quarter q), and Companies_{iia} which is the number of companies analyst i follows during the year (measured as the number of companies followed during the year by analyst i following the firm j in quarter q).

Following Clement and Tse (2003; 2005), we scale each variable to range from 0 to 1, using a transformation that preserves the relative distances between the values of each characteristic for firm j in quarter q and facilitates comparisons of regression model coefficients. We transform the analyst characteristic variables, except for $Prior_Accuracy$, as follows:

$$Characteristic_{ijq} = \frac{Raw_Characteristic_{ijq} - Raw_Characteristic \min_{jq}}{Raw_Characteristic \max_{jq} - Raw_Characteristic \min_{jq}}$$
(1)

To ensure that the forecast accuracy variable increases with higher values of the measure (0 for the least accurate forecast and 1 for the most accurate forecast), we use the following transformation for the prior forecast accuracy variable for analyst *i*:

$$Prior_Accuracy_{ijq} = \frac{prior\ forecast\ error\ \max_{jq} - prior\ forecast\ error\ \min_{jq}}{prior\ forecast\ error\ \max_{jq} - prior\ forecast\ error\ \min_{jq}}$$
(2)

3. Analyst characteristics and the timing of forecast revisions

3.1. Research design

We employ both continuous and discrete timing variables to examine the relation between analyst characteristics and timing of forecast revisions. RT is a continuous variable of revision timing and is defined as the natural logarithm of the number of days since the quarter q-l earnings announcement date. We also use discrete event time variables representing five periods between the prior-quarter and the current-quarter earnings announcement. We measure the timing of analyst forecast revisions relative to the quarter q-l and the quarter q earnings announcement dates. For each individual analyst revision of the one-quarter-ahead earnings forecast, we determine the number of trading days between the revision date and the earnings announcement date. For revisions made at or prior to the mid-point of the quarter, we measure

revision timing relative to the prior-quarter, q-1, earnings announcement (trading days 0 through 32), and for revisions made after the mid-point of the quarter, we measure revision timing relative to the current-quarter, q, earnings announcement (trading days -30 through -1). These trading days cover the entire quarter.

We then group the forecast revisions into the following five periods based on timing:

Period I = days(0, 1) (announcement period of quarter q-I earnings);

Period 2 = days(2, 6) (immediate post-announcement period of quarter q-1 earnings);

Period 3 = days (7, 32) (non-immediate post-announcement period of quarter q-1 earnings);

Period 4 = days (-30, -6) (non-immediate pre-announcement period of quarter q earnings);

Period 5 = days(-5, -1) (immediate pre-announcement period of quarter q earnings); where quarter q is the quarter for which earnings are being forecasted. Our definitions of the timing and the periods closely follow those in Ivković and Jegadeesh (2004). We refer to Periods 2 and 3 together as post-announcement periods, and Periods 4 and 5 together as pre-announcement periods.

Utilizing the continuous revision timing variable, *RT*, we estimate the following regression model:

$$RT = a0 + a1*FirmEXP + a2*GenEXP + a3*Industries + a4*Prior_Accuracy + a5*Broker Size + a6*Companies + Control variables$$
 (3)

where RT is the natural logarithm of the number of days since the quarter q-l earnings announcement date and the other variables are as defined earlier.

We also use the following logistic model to examine the determinants of issuing forecast revisions in one of the five periods (*Periods 1, 2, 3, 4*, and 5):

$$Pr(Period1=1 \text{ or } Period 2=1 \text{ or } Period 3=1 \text{ or } Period 4=1 \text{ or } Period 5=1)$$

$$= F(a0 + a1*FirmEXP + a2*GenEXP + a3*Industries + a4*Prior_Accuracy$$

$$+ a5*Broker Size + a6*Companies + Control variables)$$
(4)

3.2. Control variables

We control for information environment and other firm characteristics that may affect analyst forecast timing. Following the prior literature, we control for the days elapsed since the last forecast (Clement and Tse, 2005), the number of analysts following the firm (Stickel, 1989; Zhang, 2006), firm size (Clement and Tse, 2005; Mikhail et al., 1997), and changes in earnings per share (Lang and Lundholm, 1996; Stickel, 1989) in the multivariate analyses examining the relations among analyst characteristics, forecast revision timing, and relative forecast error. We also include frequency of analyst quarterly earnings forecasts, book-to-market ratio, earnings characteristics such as whether the firm reports negative earnings and special items, as well as the prior-quarter mean consensus forecast error as additional control variables. Specifically, we measure these variables as follows:

DaysElapsed $_{ijt}$ = days elapsed since the last forecast by any analyst following firm j. We scale the raw variable to range from 0 to 1 using a transformation that preserves the relative distances for firm j in quarter q. It is calculated as the number of days between analyst i's forecast of firm j's earnings and the most recent preceding forecast of firm j's earnings by any analyst minus the minimum number of days elapsed for analysts following the firm j in quarter q, divided by the range of days elapsed for analysts following the firm j in quarter q;

 $NumForecast_{ijq}$ = natural logarithm of the number of quarter q EPS forecasts by analyst i for firm j between quarter q-l and quarter q earnings announcement dates;

 $Size_{jq-1}$ = natural logarithm of the market value of equity at the end of quarter q-1;

 BM_{jq-1} = book value of equity divided by market value of equity at the end of quarter q-1;

 $NumAnalyst_{jq}$ = natural logarithm of the number of analysts who issue quarter q EPS forecasts for firm j between quarter q-l and quarter q earnings announcement dates;

Special_{iq-1} = COMPUSTAT special items divided by sales for quarter q-1;

 $NegEn_{jq-1}$ = one if quarter q-l EPS is negative, zero otherwise; and

 $MnFE_{jq-1}$ = analyst mean consensus forecast error for quarter q-l EPS, measured as the absolute value of (current-quarter q-l actual EPS minus the analyst mean consensus forecast for quarter q-l EPS), divided by the absolute value of quarter q-l actual EPS.

3.3. Descriptive statistics

Table 1 presents the descriptive statistics on our final sample of analyst first forecast revisions and analyst characteristics. We report descriptive statistics for all revisions, upward revisions, and downward revisions. On average, analysts revise their first forecast 19.09 trading days after the prior quarterly earnings announcement. Revision timing is longer for downward revisions, meaning that downward revisions tend to be issued later in the fiscal quarter. The mean (median) value of the magnitude of forecast revision for the full sample is -2.836% (-2.362%) of the prior forecast. On average, analysts have about 15 quarters of firm-specific experience and 29 quarters of general experience. Analysts cover about two industries classified by an I/B/E/S Industry code and 18 companies on average, and the sample mean (median) value of brokerage firm size is 70 (50). The mean (median) value of days elapsed since any analyst forecast is 6.8 (2) days. Finally, the average number of quarterly forecasts issued by an analyst is 1.63 in our sample.

To investigate whether analysts with different characteristics time their forecast revisions at different points during the fiscal quarter, we compare the means and medians of various forecast and analyst characteristics across the five event-time periods and report the results in Table 2. Panel A, which reports the results for the full sample of earnings forecast revisions, indicates a high frequency of earnings forecast revisions during $Period\ l$, the quarter q-l earnings announcement period. More than 25% of the forecast revisions are issued on the day of and the day following the quarter q-l earnings announcement. This finding is consistent with the results reported in Ivković and Jegadeesh (2004). Forecast revision (FR), measured as the percentage change in an individual analyst's quarterly forecast from the preceding forecast, is negative in all periods, and more negative as the quarter q earnings announcement approaches. This finding is consistent with the expectations management hypothesis, which posits that managers guide analyst forecasts lower before the earnings announcements, especially late in the fiscal period, so that firms can meet or beat analyst forecasts and thus avoid negative earnings surprises (e.g., Bartov et al., 2002; Matsumoto, 2002; Richardson et al., 2004).

Firm-specific and general experience (*FirmExp* and *GenExp*) are greater for analysts who revise their forecasts later in the quarter (*Periods 3, 4,* and 5). The number of industries and the number of companies an analyst follows (*Industries* and *Companies*) is greater for analysts who revise forecasts earlier in the quarter (i.e., in *Periods 1 and 2*) than for analysts who revise forecasts during the pre-announcement period (i.e., *Periods 4* and 5). Prior forecast accuracy (*Prior_Accuracy*) is higher for analysts who revise their forecasts later in the quarter (i.e., in *Periods 3, 4* and 5) and broker size (*Broker_Size*) is larger for analysts revising forecasts during the pre-announcement period (i.e., *Periods 4* and 5). Although the temporal trend is not strictly monotonic, overall, analysts who have more firm-specific and general experience and more

accurate prior-period forecasts, analysts affiliated with larger brokerage firms, and analysts who follow fewer industries and companies tend to revise their forecasts later in the quarter, i.e., during the pre-announcement period. Panel A also shows that earlier revisions tend to be made in shorter intervals and analysts who forecast later issue more forecasts in a quarter.

We also compare forecast and analyst characteristics across event-time periods for upward and downward forecast revisions separately. Panel B reports the results for upward revisions and Panel C presents the results for downward revisions. The temporal patterns of analyst characteristics for upward and downward revisions closely follow those reported in Panel A for the full sample.

3.4. Association between forecast revision timing and analyst characteristics

In this subsection, we examine the association between forecast revision timing and analyst characteristics, considering various forecast and analyst characteristics at the same time while controlling for firm characteristics. Because the residuals may be correlated across analysts and/or over time, we report test statistics and significance levels based on standard errors adjusted by a two-dimensional cluster at the analyst and quarter levels (Petersen, 2008). Table 3 reports the results of regressions using the continuous event-time variable, *RT*, and Table 4 reports the results of logistic regressions based on the five discrete event-time periods, *Periods 1* to 5.3

Using the scaled continuous event-time variable, *RT*, as a dependent variable, we present the results for all revisions, upward revisions, and downward revisions in Table 3. We find that analysts who have more general and firm-specific experience and more accurate prior-period

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³ Like Ivković and Jegadeesh (2004), we also estimate the forecast timing regressions and logistic models after excluding revisions in *Period 1*. The untabulated results are qualitatively similar to those reported in Tables 3 and 4.

forecasts, analysts affiliated with larger brokers, and analysts who follow fewer companies and industries revise their forecasts later in the quarter (i.e., during the non-immediate and immediate pre-announcement periods of quarter q earnings). These results are consistent with those reported in Table 2. The coefficient on book-to-market ratio is positive, meaning that analysts who follow growth firms revise forecasts earlier. The coefficient on mean consensus forecast error is negative, indicating that for firms reporting large unexpected EPS, analysts make their revisions relatively early. The results for the upward revisions and the downward revisions are similar to the results for all revisions, indicating that the effect of analyst characteristics on revision timing is symmetric between upward and downward revisions.

Overall, the main message from the results in Table 3 is qualitatively the same as that from Table 2. Analysts with characteristics that are positively related to absolute forecast error, as documented in prior studies (e.g., Clement, 1999; Clement and Tse, 2003), revise their forecasts later in the quarter.

Table 4 presents the results for the full sample of forecast revisions of logistic regressions with discrete event-time variables as dependent variables and forecast and analyst characteristics as explanatory variables. We estimate these models separately for each event-time period. We do not report the results for upward revisions and downward revisions because they are qualitatively similar to the results for all revisions.

We expect the signs of the explanatory variable coefficients to be the opposite of those reported in Table 3 for forecast revisions made earlier in the quarter, i.e., in *Periods 1, 2,* or *3*. Conversely, we expect the explanatory variable coefficient signs to be consistent with those in Table 3 for forecast revisions made later in the quarter, i.e., in *Periods 4* or *5*.

As expected, the signs of the coefficients on analyst characteristics for *Period 4* or *Period 5* are generally the same as those reported in Table 3, except that the coefficients on *GenEXP* and *Industries* are insignificant when *Period 5* is the dependent variable. Also as expected, the coefficients on analyst characteristics in *Period 1* are generally opposite of those in Table 3. The results with *Period 2* and *Period 3* as dependent variables suggest that some of the relations between analyst characteristics and revision timing may not be monotonic. Specifically, with *Period 3* as the dependent variable, while the coefficients on *FirmEXP* and *Broker_Size* exhibit the expected opposite sign to that in Table 3, the coefficient on *GenExp* and *Companies* have the same signs as those in Table 3. With *Period 2* as the dependent variable, the coefficients on *Industries*, *Prior_Accuracy*, and *Broker_Size* are the opposite of those in Table 3 as expected, but the coefficient on *Companies* shows the same sign as that in Table 3.

4. Forecast timing, relative forecast error, and analyst characteristics

In this section, we examine the relations between timing of forecast revisions, relative forecast error, and analyst characteristics. Specifically, we examine whether analyst characteristics are associated with relative forecast error, a measure that more closely represents analyst ability because it is purged of the timing advantage of recent forecasts. We also test whether the improvement in forecast error over event time, documented in Ivković and Jegadeesh (2004), can be attributed to analysts with different characteristics forecasting at different times during the period. Ivković and Jegadeesh examine the timing of analyst forecast revisions and the relation between the revision's timing and its information content. They posit that the sources of value contained in analyst earnings forecasts come from analysts' skill at interpreting public information and/or their ability to collect and process private information.

Based on their finding that the relative precision of analyst forecasts is lower immediately after the prior-quarter earnings announcement and greater before the current-quarter earnings announcement, Ivković and Jegadeesh conclude that the value of analyst forecasts primarily comes from analysts' ability to collect and process private information. If analyst characteristics are determinants of forecast-revision timing, however, failure to control for analyst characteristics when examining the relation between relative forecast error and revision timing may give rise to a correlated omitted variables problem.

Relative forecast error, RFE, is the difference between the forecast error of the newly released one-quarter-ahead earnings forecast and the forecast error of the consensus forecast one day before the forecast revision. The consensus forecast summarizes the information available to all analysts prior to the forecast revision, whereas the new forecast conveys the incremental information upon which the analyst revises her/his forecast. Specifically, for every new earnings forecast made by analyst i for stock j at time t, we define the relative current forecast error RFE_{ijt} as:

$$RFE_{ijt} = FE_{ijt} - CFE_{jt-1} \tag{5}$$

where $FE_{ijt} = 100 \text{ x } Abs[(analyst_forecast_{ijt} - quarterly_earnings_j) / quarterly_earnings_j]$ and $CFE_{ijt} = 100 \text{ x } Abs[(consensus_forecast_{ijt} - quarterly_earnings_j) / quarterly_earnings_j]$.

A negative (positive) value of RFE indicates that the analyst's revised forecast is more (less) accurate than the consensus forecast. Following Ivković and Jegadeesh (2004), we truncate both FE_{ijt} and CFE_{jt-1} at 100%. We compute the consensus forecast one day before the forecast revision (CFE_{jt-1}) as the arithmetic average of each analyst's last forecast since the quarter q-1 earnings announcement. Under this definition, RFE is undefined at event day 0 because we

cannot compute CFE for event day 0.4 In addition, RFE on day 1 is unavailable unless at least two analysts issue forecasts on day 0. We therefore exclude revisions in $Period\ 1$ (days $(0,\ 1)$) from the multivariate regressions of relative forecast revisions.

We employ the following two regression models, one with the continuous event-time variable and the other with the discrete event-time variables, to examine the association between relative forecast error and analyst characteristics and timing of forecast revisions:

$$RFE = a0 + a1*RT + a2*FirmEXP + a3*GenEXP + a4*Industries \\ + a5*Prior_Accuracy + a6*Broker_Size + a7*Companies + Control variables$$

$$(6)$$

$$RFE = a1*Period2 + a2*Period3 + a3*Period4 + a4*Period5 + a5*FirmEXP \\ + a6*GenEXP + a7*Industries + a8*Prior_Accuracy \\ + a9*Broker_Size + a10*Companies + Control variables$$

$$(7)$$

where Period2 (3, 4 or 5) = 1 if the forecast revision is issued in $Period\ 2$ (3, 4 or 5) and 0 otherwise.

We report the estimation results in Table 5. Model (1) employs the continuous event-time variable, *RT*, and model (2) employs the discrete event-time period variables, *Period2*, *Period3*, *Period4*, and *Period5*. Relative forecast errors are more negative for analysts with better priorperiod forecast accuracy, and who are affiliated with larger brokers and follow fewer firms. The coefficient on *GenExp* is negative and statistically significant in model (1) but insignificant in model (2). Note that characteristics that are positively (negatively) associated with revision timing in Table 3 are negatively (positively) correlated with relative forecast error in Table 5. Together, these results suggest that analyst characteristics are associated with analysts' forecasting ability and analysts with superior ability tend to forecast later in the quarter.

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 $^{^4}$ We calculate the consensus forecast based on analysts' forecasts since the quarter q-l earnings announcement date.

The coefficient on *RT* in model (1) is negative even after including analyst characteristics in the regression, indicating that relative forecast error becomes more negative later in the quarter. Thus, revisions made later in the fiscal quarter are relatively more accurate than those made earlier in the quarter, suggesting that the Ivković and Jegadeesh (2004) results are unlikely to suffer from an omitted correlated variables problem. Like Ivković and Jegadeesh, we find more negative coefficients in model (2) in Periods 4 and 5 than in Periods 2 and 3.

The untabulated results for upward revisions and downward revisions are qualitatively the same as those reported in Table 5. The significantly negative coefficient on *RT* and relatively more negative coefficients on *Period 4* and *Period 5* in the regressions including analyst characteristics as explanatory variables indicate that, while analyst characteristics are associated with relative forecast error and revision timing, factors other than analyst characteristics also affect the temporal trend of relative forecast error.

5. Sensitivity analysis

In our main analyses, our sample revisions include only the first forecast revision for each analyst after the quarter q-l earnings announcement. While this choice has many advantages as discussed in Section 3, it is not without problems. If an analyst makes a revision on the announcement date of quarter q-l earnings or the next day, the subsequent forecasts by this analyst will be excluded from the sample revisions in the later periods. It is possible that analysts with superior ability revise earnings forecasts during the q-l earnings announcement period and revise again later in the fiscal quarter. If so, our results may not fully reflect the impact of analyst characteristics on forecast revision timing and relative forecast accuracy. Because many analysts revise quarterly forecasts just once after the quarter q-l earnings

announcement, this is unlikely to be a serious concern in quarterly forecast revisions. Nonetheless, we test the sensitivity of our results to the choice of revisions included in the sample. We re-estimate regressions (3) and (6) on two additional samples, one including all forecast revisions, (i.e., *not excluding* subsequent forecast revisions of the same analysts) and the other including only the last revision for each analyst. The results are reported in Table 6.

Panel A of Table 6 presents the results with all forecast revisions. The results show that analysts with more general experience, higher prior forecast accuracy, and lower industry and company coverage, and analysts affiliated with larger brokerage firms tend to issue forecast revisions later. The coefficient on FirmExp is insignificant. 5 In the relative forecast error regression, improvement in forecast accuracy over the consensus increases as the quarter q earnings announcement approaches. Relative forecast error also decreases with GenExp, Prior Accuracy and Broker Size, and increases with Companies. Both sets of results are consistent with those reported in Tables 3 and 5. We also perform the analyses for upward revisions and downward revisions separately. The untabulated results are qualitatively the same as those obtained in the primary analysis. The results for the sample that includes only the last revision of each analyst are reported in Panel B of Table 6. These results are quite similar to those reported in Panel A and are consistent with the results in Tables 3 and 5. Again, the untabulated results for upward revisions and downward revisions separately are qualitatively the same as those obtained in the primary analysis. Taken together, the results of these sensitivity tests suggest that our primary findings are quite robust.

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⁵ As documented by Clement and Tse (2005), the insignificant coefficient on *FirmExp* is caused by multicollinearity between *FirmExp* and *GenExp*. After excluding *GenExp*, the coefficient on *FirmExp* becomes positive and significant at the 1% level.

6. Summary and conclusions

Prior research pays limited attention to the timing of analysts' forecasts as well as to the determinants of this timing. In this study, we examine the relation between analyst characteristics and the timing of forecast revisions and between analyst characteristics and relative forecast error, a measure of forecast accuracy of a revised forecast relative to the accuracy of the existing consensus forecast. We find that analysts with more firm-specific and general experience and more accurate prior-period forecasts, analysts employed by larger brokerage firms, and analysts who follow fewer industries and companies tend to forecast later in the quarter. We also find that analyst characteristics that are positively related to forecast timing are negatively associated with relative forecast error. These results suggest that analyst characteristics proxy for analysts' forecasting ability and that the temporal trend of analysts' forecast accuracy is attributable not only to the timing advantage of recent forecasts, but also to analysts with greater ability revising forecasts later in the quarter.

Our findings provide insights into the forecasting behavior of sell-side analysts by showing that analyst forecast timing is endogenously determined. These results conflict with the implicit assumption of prior empirical studies that the timing of analyst forecasts is exogenously determined. Our results are also consistent with the predictions of the analytical models in Chen (2007) and Guttman (2010), that analysts strategically decide their forecast timing.

Our study also has implications for investors who could benefit from understanding the relation between analyst characteristics and forecast accuracy. This knowledge would help them select which analyst forecast to rely on when faced with multiple forecasts from different analysts. Our results could also help investors to better understand the association between the timing of forecasts, analyst characteristics, and the relative accuracy of forecasts. They suggest

that investors should consider not only forecast accuracy, but also forecast timing, in assessing analyst ability. Finally, our findings have implications for sell-side analysts' forecast timing decisions because investor payoffs for analyst services depend on the timing of forecasts. By helping sell-side analysts understand the dynamics of forecast revision timing, our study will help analysts in formulating their forecast timing strategy.

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Table 1Descriptive Statistics of Forecast and Analyst Characteristics (unscaled)

	All revisions		Upward re	evisions	Downward	Downward revisions		
Variable	Mean	Median	Mean	Median	Mean	Median		
Number of Revisions	1.403	1	1.385	1	1.415	1		
Revision Timing	20.424	11	18.967	8	21.461	14		
Forecast Revision	-2.836	-2.362	10.686	6.849	-12.468	-8.333		
Firm Experience	15.221	10	14.908	10	15.444	10		
General Experience	29.072	24	28.822	24	29.250	25		
Number of Industries Following	2.159	2	2.089	2	2.209	2		
Prior-Period Forecast Error	0.129	0.070	0.134	0.082	0.126	0.061		
Broker Size	70.219	50	70.108	49	70.298	50		
Number of Companies Following	17.990	16	17.836	16	18.100	16		
Days Elapsed Since Last Forecast	6.834	2	6.676	2	6.948	2		
Number of Forecasts	1.628	1	1.595	1	1.652	2		

Note: This table reports descriptive statistics of unscaled forecast and analyst characteristics. Our sample consists of 242,701 quarterly analyst forecast revisions from January 1990 to December 2009, of which 100,962 are upward revisions and 141,739 are downward revisions. We classify each earnings forecast revision as an upward revision or a downward revision based on whether the revised forecast is above or below the previous forecast of the revising analyst. Data on analyst and forecast characteristics are obtained from the I/B/E/S detail tape. We restrict the sample to quarterly earnings per share (EPS) forecasts issued between the prior-quarter earnings announcement (EAD_{a-l}) and the current-quarter earnings announcement (EAD_a), and to firms followed by a minimum of two analysts. We include the first forecast revised by each analyst for a particular firm in each sample quarter. Number of Revisions is the number of forecast revisions by the analysts since EAD_{q-1} ; Revision Timing is the number of days since EAD_{q-1} ; Forecast Revision is the change in an individual analyst's quarterly EPS forecast scaled by the absolute value of the old forecast and multiplied by 100; Firm Experience is the number of quarters of firm-specific experience for each analyst; General Experience is the number of quarters of career experience for each analyst; Number of Industries Following is the number of I/B/E/S industries the analyst follows in the year; Prior-Period Forecast Error is the ratio of the absolute value of forecast error of the analyst's last EPS forecast for quarter q-1 EPS; Broker Size is the number of analysts in the analyst's brokerage firm in the year; Number of Companies Following is the number of companies the analyst follows in the year; Days Elapsed Since Last Forecast is the number of days since any analyst's prior forecast; Number of Forecasts is the number of quarterly EPS forecasts issued by the analyst since EAD_{a-1} .

Table 2Analyst Characteristics and Forecast Timing

Panel A: Mean (median) values of forecast and analyst characteristics - All forecast revisions

								Prior_	Broker_		Days-	Num-
Period	N	%	RT	FR	FirmEXP	GenEXP	Industries	Accuracy	Size	Companies	Elapsed	Forecast
1	62,010	25.55	0.025	-1.917	0.367	0.362	0.329	0.598	0.251	0.441	0.003	0.327
			(0.017)	-(1.852)	(0.267)	(0.282)	(0.250)	(0.667)	(0.180)	(0.409)	(0.000)	(0.000)
2	46,796	19.28	0.076	-2.364	0.405	0.414	0.347	0.581	0.267	0.428	0.069	0.338
			(0.039)	-(2.037)	(0.308)	(0.326)	(0.250)	(0.645)	(0.179)	(0.375)	(0.000)	(0.000)
3	58,243	24.00	0.367	-2.430	0.431	0.461	0.329	0.600	0.322	0.423	0.374	0.440
			(0.326)	-(2.151)	(0.340)	(0.396)	(0.200)	(0.667)	(0.218)	(0.364)	(0.261)	(0.693)
4	65,901	27.15	0.826	-4.384	0.439	0.459	0.319	0.622	0.376	0.424	0.381	0.445
			(0.850)	-(3.448)	(0.351)	(0.390)	(0.200)	(0.690)	(0.284)	(0.367)	(0.214)	(0.693)
5	9,751	4.02	0.988	-2.917	0.428	0.439	0.326	0.614	0.349	0.410	0.334	0.397
			(1.000)	-(1.923)	(0.333)	(0.362)	(0.200)	(0.667)	(0.250)	(0.350)	(0.182)	(0.693)
Total	242,701	100.00	0.373	-2.836	0.412	0.425	0.330	0.602	0.309	0.428	0.221	0.391
			(0.206)	-(2.362)	(0.316)	(0.341)	(0.250)	(0.667)	(0.210)	(0.379)	(0.029)	(0.000)

Panel B: Mean (median) values of forecast and analyst characteristics - Upward revisions

								$Prior_$	$Broker_$		Days-	Num-
Period	N	%	RT	FR	FirmEXP	GenEXP	Industries	Accuracy	Size	Companies	Elapsed	Forecast
1	28,151	27.88	0.025	10.350	0.368	0.359	0.333	0.570	0.246	0.439	0.003	0.306
			(0.017)	(6.667)	(0.269)	(0.279)	(0.250)	(0.600)	(0.173)	(0.400)	(0.000)	(0.000)
2	20,559	20.36	0.076	10.684	0.408	0.413	0.345	0.549	0.267	0.424	0.068	0.313
			(0.039)	(6.897)	(0.313)	(0.326)	(0.250)	(0.579)	(0.179)	(0.375)	(0.000)	(0.000)
3	23,795	23.57	0.364	10.784	0.430	0.455	0.320	0.578	0.314	0.425	0.378	0.425
			(0.319)	(6.667)	(0.338)	(0.388)	(0.167)	(0.643)	(0.206)	(0.367)	(0.267)	(0.693)
4	24,353	24.12	0.830	11.072	0.438	0.451	0.309	0.611	0.376	0.427	0.394	0.440
			(0.855)	(7.143)	(0.349)	(0.378)	(0.111)	(0.667)	(0.282)	(0.375)	(0.231)	(0.693)
5	4,104	4.06	0.988	10.153	0.430	0.429	0.313	0.616	0.352	0.408	0.330	0.387
			(1.000)	(6.397)	(0.333)	(0.342)	(0.125)	(0.667)	(0.256)	(0.347)	(0.167)	(0.693)
Total	100,962	100.00	0.349	10.686	0.410	0.418	0.326	0.579	0.302	0.429	0.212	0.371
	*		(0.155)	(6.849)	(0.314)	(0.333)	(0.200)	(0.636)	(0.203)	(0.381)	(0.000)	(0.000)

Table 2 continued

Panel C: Mean (median) values of forecast and analyst characteristics - Downward revisions

								Prior_	Broker_		Days-	Num-
Period	N	%	RT	FR	FirmEXP	GenEXP	Industries	Accuracy	Size	Companies	Elapsed	Forecast
1	33,859	23.89	0.025	-12.115	0.367	0.365	0.326	0.622	0.256	0.442	0.004	0.344
			(0.017)	-(8.333)	(0.265)	(0.286)	(0.250)	(0.667)	(0.185)	(0.412)	(0.000)	(0.000)
2	26,237	18.51	0.076	-12.588	0.403	0.415	0.349	0.606	0.267	0.430	0.069	0.357
			(0.039)	-(8.411)	(0.304)	(0.326)	(0.250)	(0.667)	(0.179)	(0.379)	(0.000)	(0.000)
3	34,448	24.30	0.370	-11.557	0.431	0.465	0.334	0.615	0.327	0.422	0.372	0.450
			(0.328)	-(7.692)	(0.341)	(0.400)	(0.222)	(0.667)	(0.226)	(0.360)	(0.250)	(0.693)
4	41,548	29.31	0.823	-13.444	0.440	0.465	0.325	0.628	0.377	0.423	0.373	0.449
			(0.846)	-(9.375)	(0.353)	(0.396)	(0.200)	(0.714)	(0.286)	(0.364)	(0.208)	(0.693)
5	5,647	3.98	0.987	-12.416	0.427	0.447	0.336	0.612	0.347	0.411	0.337	0.405
			(1.000)	-(8.000)	(0.333)	(0.375)	(0.200)	(0.667)	(0.245)	(0.351)	(0.195)	(0.693)
Total	141,739	100.00	0.391	-12.469	0.413	0.431	0.332	0.619	0.314	0.428	0.227	0.405
			(0.250)	-(8.333)	(0.318)	(0.350)	(0.250)	(0.667)	(0.214)	(0.375)	(0.037)	(0.693)

Note: This table reports descriptive statistics of scaled forecast and analyst characteristics for quarterly analyst forecast revisions in five event periods relative to the prior-quarter and the current-quarter earnings announcement dates. We classify each earnings forecast revision as an upward revision or a downward revision based on whether the revised forecast is above or below the previous forecast of the revising analyst. Data on analyst and forecast characteristics are obtained from the I/B/E/S detail tape. We restrict the sample to quarterly earnings per share (EPS) forecasts issued between the prior-quarter earnings announcement (EAD $_{q-1}$) and the current-quarter earnings announcement (EAD $_q$), and to firms followed by a minimum of two analysts. We include the first forecast revised by each analyst for a particular firm in each sample quarter. N is the number of forecast revisions in each period; RT is the number of days since EAD_{q-1} , scaled to range from 0 to 1; FR (forecast revision) is the change in an individual analyst's quarterly EPS forecast scaled by the absolute value of that analyst's previous forecast and multiplied by 100; FirmEXP (scaled firm experience) is the number of quarters of firm-specific experience for each analyst, scaled to range from 0 to 1; FIR (scaled general experience) is the number of analyst; scaled to range from 0 to 1; FIR (scaled prior-period forecast accuracy) is forecast accuracy of the analyst's last forecast for q-I quarter EPS, scaled to range from 0 to 1; FIR (scaled prior-period forecast accuracy) is forecast accuracy of the analyst's last forecast for q-I quarter EPS, scaled to range from 0 to 1; FIR (scaled prior-period forecast accuracy) is forecast accuracy of the analyst's last forecast for q-I quarter EPS, scaled to range from 0 to 1; FIR (scaled number of companies following) is the number of analysts prior forecast, scaled to range from 0 to 1; FIR F

Table 2 continued

Forecast revisions are grouped into the following five periods based on timing:

Period 1: days (0, 1) (announcement period of quarter q-1 earnings)

Period 2: days (2, 6) (immediate post-announcement period of quarter q-1 earnings)

Period 3: days (7, 32) (non-immediate post-announcement period of quarter q-1 earnings)

Period 4: days (-30, -6) (non-immediate pre-announcement period of quarter q earnings)

Period 5: days (-5, -1) (immediate pre-announcement period of quarter q earnings)

where quarter q is the quarter for which earnings are being forecasted. Trading days 0 through 32 are measured as the number of trading days relative to EAD_{q-l}, and trading days -30 through -1 are measured as the number of trading days relative to EAD_q.

Table 3Determinants of Analyst Forecast Timing - Regression Analysis

	All re	evisions		Upwa	rd revisions		Downw	ard revision	ıs
	Parameter			Parameter			Parameter		
Variables	estimate	t-value		estimate	t-value		estimate	t-value	
Intercept	0.921	68.5	***	0.865	52.89	***	0.953	63.15	***
FirmEXP	0.013	3.00	**	0.020	3.80	***	0.010	1.90	*
GenEXP	0.042	5.97	***	0.028	3.67	***	0.049	6.64	***
Industries	-0.014	-2.79	**	-0.019	-3.47	**	-0.010	-1.86	*
Prior Accuracy	0.034	13.56	***	0.048	12.33	***	0.020	6.89	***
Broker Size	0.109	13.4	***	0.109	12.39	***	0.108	11.84	***
Companies	-0.031	-4.90	***	-0.020	-2.81	**	-0.037	-5.58	***
DaysElapsed	0.484	30.54	***	0.514	35.90	***	0.462	26.22	***
NumForecast	-0.109	-16.39	***	-0.108	-14.32	***	-0.111	-15.47	***
Size	0.020	2.58	**	0.028	3.41	**	0.011	1.38	
BM	0.005	2.80	**	0.011	5.08	***	0.002	1.11	
NumAnalyst	0.009	1.24		0.002	0.28		0.008	1.05	
Special	-0.015	-0.43		0.021	0.33		-0.031	-0.77	
NegEn	-0.021	-3.50	***	-0.001	-0.19		-0.033	-4.55	***
MnFE	-0.089	-8.80	***	-0.088	-7.13	***	-0.080	-6.65	***
N		242,701			100,962			141,739	
Adjusted R-squared		0.267			0.289			0.252	

Note: This table reports the results of the following regression of forecast revision timing (*RT*) on analyst characteristics and control variables:

 $RT = a0 + a1*FirmEXP + a2*GenEXP + a3*Industries + a4*Prior_Accuracy + a5*Broker_Size + a6*Companies + a7*DaysElapsed + a8*NumForecast + a9*Size + a10*BM + a11*NumAnalyst + a12*Special + a13*NegEn + a14*MnFE.$

Size is the natural logarithm of the market value of equity of the firm at the end of quarter q-l; BM is the book value of equity divided by the market value of equity at the end of quarter q-l; NumAnalyst is the natural logarithm of the number of analysts following the firm between quarter q-l and quarter q-and quarter q-l and quarter q-l is a dummy variable that equals 1 if quarter q-l EPS is negative, and 0 otherwise; MnFE is analyst mean consensus forecast error for quarter q-l EPS. All other variables are defined in Table 2. All test statistics and significance levels are calculated based on standard errors adjusted by a two-dimensional cluster at the analyst and quarter levels. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

Table 4Determinants of Analyst Forecast Timing – Logistic Regressions

	Pr(Period 1 = 1)		$Pr(Period\ 2=1)$		Pr(Pe	Pr(Period 3 = 1)		Pr(Per	riod 4 = 1	<u>)</u>	Pr(Per	riod 5 = 1)		
	Parameter	Chi-		Parameter	Chi-		Parameter	Chi-		Parameter	Chi-		Parameter	Chi-	
Variables	estimate	square		estimate	square		estimate	square		estimate	square		estimate	square	
Intercept	-2.772	-14.48	***	0.711	4.95	***	-0.961	-6.14	***	-1.571	-12.87		-3.737	-26.23	***
FirmEXP	0.011	0.24		-0.055	-1.61		-0.091	-2.68	**	0.092	3.02	**	0.100	2.23	**
GenEXP	-0.627	-7.88	***	0.012	0.23		0.378	7.33	***	0.212	4.45	***	0.008	0.14	
Industries	0.069	1.58		0.073	1.88	*	-0.049	-1.31		-0.102	-3.09	**	0.026	0.58	
Prior_Accuracy	-0.108	-4.98	***	-0.161	-9.65	***	-0.028	-1.47		0.227	13.47	***	0.105	3.04	**
Broker Size	-0.404	-5.44	***	-0.516	-8.10	***	-0.142	-2.76	**	0.664	13.78	***	0.276	3.96	***
Companies	0.435	6.49	***	-0.092	-1.89	*	-0.148	-3.15	**	-0.111	-2.58	**	-0.236	-4.33	***
DaysElapsed	-32.876	-22.49	***	-3.051	-20.84	***	1.513	15.29	***	1.643	26.35	***	0.794	12.25	***
NumForecast	0.893	15.76	***	-0.325	-5.96	***	-0.098	-2.89	**	-0.271	-7.55	***	-0.336	-7.10	***
Size	-0.473	-10.90	***	-0.180	-3.60	***	0.347	7.04	***	0.304	6.53	***	-0.025	-0.48	
BM	0.087	5.12	***	-0.074	-4.26	***	-0.050	-4.37	***	0.039	3.52	***	0.124	7.71	***
NumAnalyst	-0.061	-1.25		0.060	1.13		-0.106	-3.47	**	0.124	2.39	**	0.106	2.59	**
Special	0.732	1.42		0.098	0.30		-1.001	-2.46	**	0.020	0.07		-0.043	-0.10	
NegEn	0.206	2.51	**	0.078	1.22		-0.099	-2.27	**	-0.186	-4.14	***	-0.004	-0.05	
MnFE	0.595	5.83	***	0.155	2.64	**	-0.043	-0.68		-0.604	-8.38	***	-0.143	-1.37	
N		242,701			242,701			242,701			242,701			242,701	
Pseudo R-squared		0.372			0.083			0.062			0.085			0.018	

Note: This table reports the results of the following logistic regressions designed to examine the association between forecast timing and analyst characteristics:

 $Pr(Period1=1 \ or \ Period\ 2=1 \ or \ Period\ 3=1 \ or \ Period\ 4=1 \ or \ Period\ 5=1) = F(a0+a1*FirmEXP+a2*GenEXP+a3*Industries +a4*Prior_Accuracy +a5*Broker_Size+a6*Companies+a7*DaysElapsed+a8*NumForecast+a9*Size+a10*BM+a11*NumAnalyst+a12*Special+a13*NegEn+a14*MnFE).$

Forecast revisions are grouped into the following five periods based on timing: [Period 1: days (0, 1) (announcement period of quarter q-1 earnings); Period 2: days (2, 6) (immediate post-announcement period of quarter q-1 earnings); Period 3: days (7, 32) (non-immediate post-announcement period of quarter q-1 earnings); Period 4: days (-30, -6) (non-immediate pre-announcement period of quarter q earnings)] where quarter q is the quarter for which earnings are being forecasted. Trading days 0 through 32 are measured as the number of trading days relative to the prior-quarter earnings announcement date (EAD_{q-1}) , and trading days -30 through -1 are measured as the number of trading days relative to the current-quarter earnings announcement (EAD_q) . The dependent variable *Period 1* (*Period 2, Period 3, Period 5*) equals 1 if the forecast revision is issued during Period 1 (Period 2, Period 3, Period 4, Period 5), and 0 otherwise. All other variables are defined in Tables 2 and 3. All test statistics and significance levels are calculated based on standard errors adjusted by a two-dimensional cluster at the analyst and quarter levels. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

Table 5Relation between Relative Forecast Error, Forecast Timing, and Analyst Characteristics

	Me	odel (1)		M	odel (2)	
	Parameter	` `		Parameter	•	
Variables	estimate	t-value		estimate	t-value	
Intercept	0.082	0.22				
RT	-4.597	-23.57	***			
Period2				-0.816	-2.30	**
Period3				-2.238	-5.92	***
Period4				-5.601	-14.34	***
Period5				-4.798	-11.08	***
FirmEXP	0.012	0.09		0.028	0.21	
GenEXP	-0.270	-1.76	*	-0.219	-1.44	
Industries	-0.131	-1.09		-0.156	-1.32	
Prior Accuracy	-1.548	-12.99	***	-1.492	-12.55	***
Broker Size	-0.831	-4.30	***	-0.708	-3.71	***
Companies	0.400	2.84	**	0.394	2.86	**
DaysElapsed	0.659	5.27	***	0.578	4.57	***
NumForecast	-1.374	-7.82	***	-1.097	-6.45	***
Size	-1.461	-7.89	***	-1.186	-6.67	***
BM	0.677	10.99	***	0.700	11.53	***
NumAnalyst	-0.596	-3.05	**	-0.542	-2.94	**
Special	-0.866	-0.39		-0.945	-0.43	
NegEn	1.268	4.05	***	1.182	3.79	***
MnFE	0.323	0.74		0.233	0.53	
N		180,691			180,691	
Adjusted R-						
squared		0.026			0.050	
t-test comparing coeffic	cients on:				p-values	
Period2 and Period3					<.001	
Period2 and Period4					<.001	
Period2 and Period5					<.001	
Period3 and Period4					<.001	
Period3 and Period5					<.001	
Period4 and Period5					<.001	

Table 5 continued

Note: This table reports the results of the following regressions of relative forecast error (*RFE*) on forecast timing and analyst characteristics:

```
\label{eq:model} \begin{subarray}{ll} Model (1): $RFE=a0+a1*RT+a2*FirmEXP+a3*GenEXP+a4*Industries+a5*Prior\_Accuracy+a6*Broker\_Size+a7*Companies+a8*DaysElapsed+a9*NumForecast+a10*Size+a11*BM+a12*NumAnalyst+a13*Special+a14*NegEn+a15*MnFE \end{subarray}
```

```
\label{eq:model} \begin{tabular}{ll} Model (2): $RFE=a0+a1*Period2+a2*Period3+a3*Period4+a4*Period5+a5*FirmEXP+a6*GenEXP+a8*Prior\_Accuracy+a9*Broker\_Size+a10*Companies+a11*DaysElapsed+a12*NumForecast+a13*Size+a114*BM+a15*NumAnalyst+a16*Special+a17*NegEn+a18*MnFE \end{tabular}
```

RFE (relative forecast error) is the absolute value of an individual analyst's forecast error minus the absolute value of the mean consensus forecast error measured one day before the analyst's forecast revision. The consensus forecast is measured as the average of each analyst's most recent forecast issued after EAD_{q-l} . All other variables are defined in Tables 2- 4. Model (1) measures event time as a continuous variable and the Model (2) measures event time as a discrete variable. All test statistics and significance levels are calculated based on standard errors adjusted by a two-dimensional cluster at the analyst and quarter levels. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively (two-tailed).

 Table 6

 Determinants of Analyst Forecast Timing using Alternative Forecast Revision Samples

Panel A: Sample includes all analyst forecast revisions

	Depende	nt Variable = RT	Dependen	t Variable = RFE
	Parameter	<u> </u>	Parameter	
Variables	estimate	t-value	estimate	t-value
Intercept	0.489	27.86***	-1.765	-3.88***
RT			-4.724	-25.77***
FirmEXP	0.004	1.21	-0.037	-0.27
GenEXP	0.014	2.79**	-0.576	-3.22 **
Industries	-0.011	-2.89**	-0.137	-1.01
Prior Accuracy	0.026	13.55 ***	-1.632	-12.94***
Broker Size	0.057	10.42 ***	-0.790	-3.98 ***
Companies	-0.014	-2.97**	0.466	2.79**
DaysElapsed	0.328	31.68***	0.908	8.37***
NumForecast	-0.085	-20.24***	-1.270	-6.38***
Size	0.192	30.27***	-1.468	-7.64 ***
BM	0.001	0.65	0.860	12.29***
NumAnalyst	0.007	1.26	-0.421	-1.73*
Special	0.003	0.10	0.779	0.35
NegEn	-0.003	-0.64	1.505	5.01 ***
MnFE	-0.060	-8.46***	1.118	2.40 **
N		402,879		339,936
Adjusted R-squared		0.195		0.028

Table 6 continued

Panel B: Sample includes only the last analyst forecast revisions

	Depende	ent Variable = RT	Dependen	t Variable = RFE		
	Parameter		Parameter			
Variables	estimate	t-value	estimate	t-value		
Intercept	0.482	28.55***	-3.435	-7.09***		
RT			-2.606	-12.96***		
FirmEXP	0.006	1.75*	0.001	0.01		
GenEXP	0.004	0.9	-0.547	-3.12**		
Industries	-0.014	-4.06***	-0.105	-0.83		
Prior Accuracy	0.032	16.29***	-1.821	-13.59***		
Broker Size	0.005	0.99	-0.469	-2.51**		
Companies	-0.010	-2.36**	0.476	3.03 **		
DaysElapsed	0.255	33.44 ***	0.828	6.89***		
NumForecast	-0.086	-21.17***	-1.327	-6.52***		
Size	0.456	48.88***	-3.282	-15.01***		
BM	0.003	1.77*	0.982	13.23 ***		
NumAnalyst	0.011	1.95*	-0.469	-1.84*		
Special	-0.001	-0.03	0.645	0.28		
NegEn	-0.013	-2.51 **	1.884	6.69***		
MnFE	-0.070	-10.13 ***	0.925	1.94*		
N		300,693		261,228		
Adjusted R-squared		0.391	0.032			

Note: The table reports the results of the following regressions of forecast revision timing (RT) on analyst characteristics and control variables, and of relative forecast error (RFE) on forecast timing and analyst characteristics:

```
RT = a0 + a1*FirmEXP + a2*GenEXP + a3*Industries + a4*Prior\_Accuracy + a5*Broker\_Size \\ + a6*Companies + a7*DaysElapsed + a8*NumForecast + a9*Size + a10*BM + a11*NumAnalyst \\ + a12*Special + a13*NegEn + a14*MnFE
```

```
RFE = a0 + a1*RT + a2*FirmEXP + a3*GenEXP + a4*Industries + a5*Prior\_Accuracy \\ + a6*Broker\_Size + a7*Companies + a8*DaysElapsed + a9*NumForecast + a10*Size \\ + a11*BM + a12*NumAnalyst + a13*Special + a14*NegEn + a15*MnFE
```

Panel A presents the results based on a sample that includes *all* analyst forecast revisions during the quarter and Panel B presents the results based on a sample that includes only the *last* forecast revision by each analyst during a quarter. All variables are defined in Tables 2-5. All test statistics and significance levels are calculated based on standard errors adjusted by a two-dimensional cluster at the analyst and quarter levels. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively (two-tailed).