Coverage changes and earnings forecast accuracy

Abstract

We examine the effect on earnings forecast accuracy when financial analysts add or drop coverage. We find that the accuracy of analysts' *first* forecast for a firm (newly added coverage) is lower relative to their peers. In addition, the accuracy of their *last* forecast (just before coverage is dropped) is also lower relative to their peers. Further analysis shows that our results are not driven by the rookie analysts (analysts with less than one-year experience) or retiring analysts (i.e., analysts who are within their final year before retiring).

Keywords: Earnings Forecasts; Financial Analysts; Forecast Accuracy; Coverage Initiation; Coverage Termination.

JEL classification: M41; G17; G29

Coverage changes and earnings forecast accuracy

1. Introduction

The forecast of earnings per share (EPS) is a key ingredient to security valuation models, and there is a longstanding interest in the determinants and characteristics associated with EPS forecast accuracy.[1] Prior research has found that financial analyst characteristics such as past forecast accuracy, forecasting experience, number of firms followed, and the size of their broker firm affect forecast accuracy (e.g., Brown 2001; Clement 1999; Jacob, Lys, and Neale 1999; Clement and Tse 2005). In this paper, we investigate whether forecast accuracy is higher or lower when an analyst adds or drops coverage for a firm (i.e., their first and last forecast), relative to their peer analysts[2].

The effect on EPS forecast accuracy when analysts add or drop coverage is contentious. On the one hand, Mikhail, Walther, and Willis (2003) and Jacob, Lys, and Neale (1999) find that higher firm-specific experience generally correlates with higher forecast accuracy. This suggests that the first forecast of an analyst would be less accurate, while their last forecast would be more accurate.

On the other hand, McNichols and O'Brien (1997) predict the opposite result. They hypothesize that analysts exert extra effort when issuing their first forecast, whereas their last forecast is associated with sample selection bias (i.e., analysts drop coverage when they

[1] See, for example, Brown (1993), Stickel (1993), Sinha, Brown, and Das (1997), and Cheong and Thomas (2011). For an excellent overview of the literature, see Ramnath, Rock, and Shane (2008).

[2] Throughout the paper, the peer analysts refer to the analysts who follow the same firm at the same time when analysts' coverage changes.

are no longer accurate). Consistent with their hypothesis, they find that "forecasts for newly added stocks are more accurate ... while forecasts for dropped stocks are less accurate" (p. 187).

We find that both streams of conflicting literature are only partially correct (and partially wrong). Using analysts' quarterly earnings forecasts from the I/B/E/S database from 1985 to 2012, we find the forecast accuracy to be lower in both cases. That is, when an analyst adds or drops coverage for a firm (i.e., their first and last forecast), their forecast accuracy is generally lower, relative to their peer analysts.

Our research design differs from McNichols and O'Brien (1997) in the following three ways. First, we use a paired-sample analysis, where we compare the forecast accuracy between an analyst and their peer analysts for the *same* firm and at the *same* time. Thus, our results are not affected by confounding firm-effects or year-effects. Second, our results are robust to both univariate and multivariate regression analysis, which takes into account various analyst characteristics affecting forecast accuracy. As a contrast, McNichols and O'Brien (1997, Table 4) use only simple univariate analysis, and unpaired two-sample test.[3] Third, following Clement and Tse (2005), we scale our forecast accuracy variable to range between zero and one. Thus, our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error.

In addition, we consider various alternative hypotheses for our findings. First, we examine whether our finding of less accurate forecasts from analysts who add or drop

---

[3] Note that the number of observations in McNichols and O'Brien (1997, Table 4) differs across the sample classification.

coverage is related to the rookie or retiring analysts. We define a forecast as made by a rookie (retiring) analyst if that forecast is made in the first (last) year that the analyst appears in the I/B/E/S database.

Using regression analysis, our main results continue to hold after controlling for the effect of rookie and retiring analysts. Interestingly, even though the rookie analysts are generally less accurate, we find that the first forecast of a rookie analyst is actually more accurate (inferred from the interaction term of first forecast and rookie analyst dummies). Likewise, even though retiring analysts are generally less accurate, we find that the last forecast of a retiring analyst is more accurate. It appears as though rookie analysts want to make a good "first impression", whereas retiring analysts want to leave a good "final legacy".

Finally, we examine the alternative hypothesis that the lower accuracy for added coverage is due to analysts who add coverage of firms from their non-primary industries. The assumption here is that an analyst has greater expertise in his primary industry, and would find it more difficult to predict earnings for firms outside his primary industry.

Using regression analysis, we find our main results unaffected by analysts who add coverage of firms from their non-primary industries. Interestingly, even though the forecasts of firms outside their primary industries tend to be less accurate[4], their first forecast in the non-primary industries tend to be more accurate. This suggests that analysts tend to pay more attention to the newly added firm to compensate for their non-proficiency of the industry knowledge.

---

[4] Our result is consistent with Brown, Call, Clement, and Sharp (2015), who found industry knowledge to be an important input to analysts' earnings forecast.

In terms of contributions, we conduct a careful and comprehensive investigation of the forecast accuracy of analysts who add or drop coverage relative to their peer analysts. In addition, we consider alternative explanations, and examine how rookies, retiring analysts, and coverage of non-primary industries affect our results. Our findings are important to investors and financial analysts. For example, they can significantly improve the accuracy of their valuation models by simply eliminating any newly added EPS forecasts when computing the consensus EPS forecasts. Finally, prior research suggests that higher analyst coverage decreases information asymmetry between the investors and managers of the firm (e.g., Yu 2008; Schutte and Unlu 2009; Sun 2009). Paradoxically, our results suggest important nuances to those studies, since added (dropped) coverage *initially* increases (decreases) information asymmetry, as measured by the magnitude of consensus forecast error. In other words, because the forecasts from added coverage are less accurate than the existing forecasts, the increased analyst coverage results in the consensus forecast being less accurate, thereby increasing the information asymmetry. And because the forecasts from the dropped coverage are less accurate than the remaining forecasts, the decreased analyst coverage results in the consensus forecast being *more* accurate, thereby decreasing the information asymmetry.

The paper is organized as follows. We review the literature and develop hypothesis in section 2. In section 3, we describe the data used in the analyses and present the research design and variable definitions. The results are reported and discussed in section 4. Further analysis is shown in section 5. Finally, section 6 summarizes results and offers conclusions.

2. Prior Literature and Hypothesis Development

We review prior literature and develop hypotheses in this section.

2.1 Forecast Accuracy and Experience

Prior literature documents the relationship between forecast accuracy and analysts' experience. In general, research finds that more experienced analysts issue more bold and accurate forecasts than inexperienced analysts. Hong, Kubik, and Solomon (2000) show that inexperienced analysts are less likely to issue bold forecasts and they are more likely to be fired due to inaccurate forecasts. Mikhail, Walther, and Willis (2003) and Jacob, Lys, and Neale (1999) find that analysts' forecast accuracy is positively associated with their experience. Clement (1999) shows that forecast accuracy increases as analysts have more general and firm-specific experience.

2.2 Analysts' Following and Dropping Firms and Forecasts' Accuracy

Research suggests that analysts' choice of the firms that they follow is strategic since their compensation is based on the ability to forecast the performance firms accurately (Emery and Li 2009; Hong, Kubik, and Solomon 2000; Mikhail, Walther, and Willis 1999; Stickel 1992). Li, Rau, and Xu (2009) focus on the different stages of Institutional Investor all-stars analysts' career. They show that prior to being selected as star analysts, analysts are likely to follow the firms that have low level of discretionary accruals. However, once recognized as all-star analysts they are more likely to follow firms that have high level of discretionary accruals.

McNichols and O'Brien (1997) explore analysts' choice of firms to follow, and suggest that when analysts add coverage of a firm, their favoritism for the newly added firm motivates the analysts to spend more time researching the firm before making their first

EPS forecasts. Given documented positive relationship between forecast accuracy and experience, it is an empirical question whether the EPS forecast accuracy of newly added coverage is higher or lower relative to their peer analysts.

Similarly, it is also unclear whether the EPS forecast accuracy of dropped firms is more or less accurate relative to their peers. McNichols and O'Brien (1997) suggests that when analysts stop following a firm, analysts' pessimism on the dropped firm discourages the analysts from allocating their time to research the firm before issuing their last EPS forecasts. However, there can be an alternate explanation why analysts drop a firm. For instance, Li, Rau, and Xu (2009) show that some superior analysts drop the easy firms to forecast and add the difficult firms to forecast.

Therefore, it is an empirical question how analysts' coverage decision is associated with the analyst's forecast accuracy relative to their peer analysts who follow the same firm. Hence, we develop the following hypotheses:

Hypothesis 1a: Analysts who add coverage of a firm attain higher/lower EPS forecast accuracy for that firm relative to their peer analysts who follow the same firm.

Hypothesis 2a: Analysts who drop coverage of a firm attain higher/lower EPS forecast accuracy for that firm relative to their peer analysts who follow the same firm.

When the analyst is a rookie (i.e., analysts with less than one-year experience), she might be highly motivated to issue an accurate forecast to compensate for the lack of experience. On the other hand, due to lack of experience, a rookie analyst might issue inaccurate forecasts.

Mikhail, Walther, and Willis (1999) find poorly performing analysts are more likely to be retiring (i.e., analysts who leave the I/B/E/S sample or analysts who are within their final year before retiring) in the following year. However, it does not necessarily mean that the analysts who are retiring issue less accurate forecasts relative to peer analysts who follow the same firm since there are analysts who finish analysts career due to the various reasons (i.e. analysts reach the retirement age or analysts resign voluntary). This leads to the following hypotheses.

Hypothesis 1b: Rookie analysts who add coverage of a firm attain higher/lower EPS forecast accuracy for that firm relative to their peer analysts who follow the same firm.

Hypothesis 2b: Retiring analysts who drop coverage of a firm attain higher/lower EPS forecast accuracy for that firm relative to peer analysts who follow the same firm.

3. Data, variables, and empirical models

In section 3, we describe our data, define the variables, and regression models.

3.1 Data

The analysis is based on I/B/E/S forecasts of quarterly earnings (specifically, one-quarter-ahead earnings forecast, FPI=6) from 1985 to 2012 (28 years) for the firms that had an increase (decrease) in their analyst following. Observations are eliminated from the sample if only one analyst follows the firm, because we need to compare analysts' forecast accuracy for our matched sample analysis. The last forecast an analyst issues in a particular quarter is used to make sure that we include one forecast from an analyst for a firm at each quarter. These procedures yield a sample of 777,098 (641,247) analyst-firm-quarter observations for the analyst's adding (dropping) coverage of a firm.

3.2 Dependent and control variables

The dependent variable in our regression models is a measure of analyst's EPS forecast accuracy. To measure analyst's forecast accuracy, we define first AFE_{ijt} as the absolute forecast error of analyst i for firm j in quarter t (= |forecasted EPS – actual EPS|). Then, consistent with Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy:

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

We scale forecast accuracy (ACC) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error.

When analyst i's forecast accuracy (ACC_{ijt}) for firm j in quarter t is the highest (lowest) among the peer analysts who follow the same firm at the same time, then ACC_{ijt} has the value of one (zero). For example, there are 48 analysts following Apple Inc. for the fiscal quarter ending Dec 31, 2010. The actual EPS is 6.43, announced on Jan 18 2011. On Jan 14, 2011, an analyst (ID: 47225) issue a EPS forecast of 5.75, corresponding to an *AFE* of 0.68. Across all analysts, the minimum (maximum) *AFE* is 0.41 (1.50). By normalizing *AFE*, we define that analyst's forecast accuracy for that fiscal quarter as 0.752 (= (1.50 – 0.68) / (1.50 – 0.41)).

Turning to the control variables, prior literature has found several analysts' characteristics that affect forecast accuracy. We include the set of characteristics such as prior accuracy, broker size, number of firms followed, number of industries followed, general experience, firm-related experience, frequency of forecasts, and forecast horizon to the quarter-end. *BROKERSIZE* is the size of broker employing the analyst, measured as the number of analysts employed by the broker. *FREQUENCY* is the number of forecasts made by the analyst for the firm in that quarter. *NFIRM* is the number of firms followed by the analyst in that year. *INDUSTRY* is the number of industries (as measured by two-digit SIC code) followed by the analyst in that year. *HORIZON* is a measure of forecast staleness, defined as the number of days from forecast issuance date to the firm's fiscal quarter end date. *GENEXP* is the overall years of forecasting experience of the analyst. *FIRMEXP* is the number of years of experience of the analyst with the firm.

All variables are scaled to range from zero to one, following Clement and Tse (2005, p.314):

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\ min_{jt}}{Raw\_Characteristic\ max_{jt} - Raw\_Characteristic\ min_{jt}}$$

where *Raw_Characteristic* $\min_{jt}$ and *Raw_Characteristic* $\max_{jt}$ are minimum (maximum) raw characteristics across all analysts following firm *j* in quarter *t*. This defines analyst *i*'s high (low) score as a high (low) value on a characteristic relative to other analysts who follow firm *j* in quarter *t*. For example, when analyst i's general experience ($GENEXP_{ijt}$) for firm *j* in quarter *t* is the highest (lowest) among the peer analysts who follow the same firm at the same time, then $GENEXP_{ijt}$ has the value of one (zero).

3.3 Empirical models

We construct the regression models following Clement (1999), Jacob, Lys, and Neale (1999), and Clement and Tse (2005) to see the relationship between forecast accuracy and coverage change after controlling analysts' characteristics. In addition, our regression models include fixed effects to capture the constant effects of analyst and year. More specifically, the analyst fixed effect captures the time-invariant analysts' characteristics that do have little variation or change slowly as time proceeds such as analysts' learning ability.

Further, we control for time effect to avoid the situation in which special events and unexpected variation can affect the analyst forecast behavior.

First, we investigate our hypothesis 1a whether the analysts' adding coverage of a firm is associated with analysts' forecast accuracy, relative to the peer analysts who follow the same firm, after controlling the factors known to affect forecast accuracy.

Since our emphasis is on the forecast accuracy of analysts who start following the firm, rather than that of the existing analysts who follow the same firm, we add a dummy variable, ADD_{ijt} to the model. The value of ADD_{ijt} is 1 if analyst i starts to follow firm j in each quarter t (zero otherwise).

$$ACC_{ijt} = \beta_0 + \beta_1 ADD_{ijt} + \beta_2 FREQUENCY_{ijt} + \beta_3 BROKERSIZE_{ijt} + \beta_4 NFIRM_{ijt} + \beta_5 INDUSTRY_{ijt} + \beta_6 FIRMEXP_{ijt} + \beta_7 GENEXP_{ijt} + \beta_8 HORIZON_{ijt} + \varepsilon_{ijt}$$

The coefficient on ADD_{ijt}, measures the average difference in forecast accuracy of analysts who add coverage of the firm, relative to the peer analysts who follow the same firm. We do not expect a specific sign of coefficient on ADD_{ijt}. It is because analysts who add coverage of a firm might spend more time researching on the firm, these analysts might be more accurate relative to peers. On the other hand, even though the analysts who just start following a firm spend more time researching on the firm, analysts' firm-specific experience can still be an important factor in explaining forecast accuracy.

As for the control variables, the expected sign of the coefficient on *FREQUENCY* should be positive since analysts who frequently issue forecasts may be the diligent analysts paying more attention to the following firms. The expected sign of coefficient on *NFIRM* and *INDUSTRY* are both negative because the broad coverage of firms or industries increases analysts' workload, thereby decreasing their forecast accuracy. Regarding the sign for forecast experience, we expect that experience will be positively associated with the forecast accuracy, which is consistent with the prior literature.

Next, we examine our hypothesis 1b to investigate whether rookie analysts' adding coverage of a firm is associated with analysts' forecast accuracy relative to peer analysts, considering the existing peer analysts who have been following the same firm, after controlling the factors known to affect forecast accuracy.

$$ACC_{ijt} = \beta_0 + \beta_1 ADD_{ijt} + \beta_2 ROOKIE_{it} + \beta_3 ADD_{ijt}*ROOKIE_{it} + \beta_4 FREQUENCY_{ijt} + \beta_5 BROKERSIZE_{ijt} + \beta_6 NFIRM_{ijt} + \beta_7 INDUSTRY_{ijt} + \beta_8 FIRMEXP_{ijt} + \beta_9 GENEXP_{ijt} + \beta_{10} HORIZON_{ijt} + \varepsilon_{ijt}$$

We construct our regression model by adding dummy and interaction variables, $ROOKIE_{it}$, ADD_{ijt}, and $ADD_{ijt}*ROOKIE_{it}$ to the Clement and Tse (2005)'s model. $ROOKIE_{it}$ reveals how analyst's forecast accuracy is associated with her first-year experience as an analyst. We define an interaction term, $ADD_{ijt}*ROOKIE_{it}$, which captures whether the forecast accuracy of analysts who start following a firm depends on the experience as an analyst relative to their peer analysts. The value of $ROOKIE_{it}$ is 1 if analyst *i* appears in the I/B/E/S for the first time (zero otherwise).

Hypothesis 2a examines whether the analysts' dropping coverage of a firm is associated with the analyst EPS forecast accuracy relative to the peer analysts who follow the same firm, after controlling the factors known to affect the forecast accuracy.

$$ACC_{ijt} = \beta_0 + \beta_1 DROP_{ijt} + \beta_2 LAGACC_{ijt} + \beta_3 FREQUENCY_{ijt} + \beta_4 BROKERSIZE_{ijt} + \beta_5 NFIRM_{ijt} + \beta_6 INDUSTRY_{ijt} + \beta_7 FIRMEXP_{ijt} + \beta_8 GENEXP_{ijt} + \beta_9 HORIZON_{ijt} + \varepsilon_{ijt}$$

We add a dummy variable, $DROP_{ijt}$ to the existing model because we are interested in examining the forecast accuracy of the analysts who drop following a firm, rather than that of remaining analysts who follow the firm. The value of $DROP_{ijt}$ is 1 if analyst *i* stops following firm *j* at quarter *t+1* (zero otherwise). This dummy variable measures the average effect of analysts who drop coverage of a firm on their forecast accuracy, relative to the peer analysts who continuously follow the firm.

We examine Hypothesis 2b to investigate whether retiring analysts' (equivalently, analysts who leave the I/B/E/S sample permanently) dropping coverage is related to analysts' forecast accuracy, considering the remaining peer analysts, after controlling the factors known to affect forecast accuracy.

$$ACC_{ijt} = \beta_0 + \beta_1 DROP_{ijt} + \beta_2 RETIRE_{it} + \beta_3 DROP_{ijt}*RETIRE_{it} + \beta_4 LAGACC_{ijt} + \beta_5 FREQUENCY_{ijt} + \beta_6 BROKERSIZE_{ijt} + \beta_7 NFIRM_{ijt} + \beta_8 INDUSTRY_{ijt} + \beta_9 FIRMEXP_{ijt} + \beta_{10} GENEXP_{ijt} + \beta_{11} HORIZON_{ijt} + \varepsilon_{ijt}$$

We modified Clement and Tse (2005)'s model by employing dummy and interaction variables, $DROP_{ijt}$, $RETIRE_{it}$, and $DROP_{ijt}*RETIRE_{it}$ to investigate the forecast accuracy of retiring analysts who drop following a firm, rather than that of remaining analysts who follow the firm. The value of $RETIRE_{it}$ equals 1 if an analyst leaves the I/B/E/S permanently in the following quarter $t+1$ (zero otherwise). $RETIRE_{it}$ measures the average effect of retiring analysts on their forecast accuracy. We define an interaction term, $DROP_{ijt}*RETIRE_{it}$, which captures whether the forecast accuracy of an analyst who stops following a firm depends on his departure from the I/B/E/S.

4. Empirical results

This section reports descriptive statistics, univariate, and multivariate results on analysts' forecast accuracy when analysts make a coverage change.

4.1 Descriptive statistics

Table 1 provides the sample selection and descriptive statistics. Panel A reports the sample selection by year and coverage change, separately for coverage added and dropped. Panel B reports the descriptive statistics that show the distribution of raw analyst characteristics.

To examine the whether analysts' adding coverage is related to their forecast accuracy, we first identify the quarter of an analyst's initial EPS forecast for a firm. Then, we compare her initial forecast accuracy for a firm with her peers who have been following the same firm.

To measure the impact of analysts' dropping coverage on their forecast accuracy, we identify the quarter of an analyst's last EPS forecast available for a firm. Since we cannot exactly determine the date when an analyst stops covering a firm, we assume that last forecast for the firm is most reflected by the analyst's dropping coverage. Once we determine an analyst's last forecast for a firm, then we compare the forecast accuracy of the firm with her remaining peers.

As time proceeds, the frequency of analysts' coverage change steadily increases for 28 years. Through out the sample period, the ratio between sample forecasts and matched forecasts are approximately one to five except for some earlier periods. For the analyst's adding coverage, about 15 percent of the analysts' forecasts are from the analysts who start to cover a firm. Also, about 85 percent of the analysts' forecasts are from the peer analysts who have been following the same firms. The similar composition is also observed for the sample of the analyst's dropping coverage. About 14 percent of the analysts' forecasts are from the analysts who stop following a firm. About 86 percent of analysts' forecasts are from the remaining peer analysts.

Panel B finds that analysts follow an average of nearly 17 firms for a year (*NFIRM*). The analysts' average general experience (*GENEXP*) and firm related experience (*FIRMEXP*) are about six years and three years, respectively. On average, analysts issue about one forecast for a firm-quarter (*FREQUENCY*). More than half of the analysts issue only one forecast for a firm-quarter, as the median forecast frequency is one. There are two notable exceptions. First, the average size of a broker, as measured by the number of analysts employed in a broker (*BROKERSIZE*), is larger than the median size. Thus, this sample contains some very large firms. Second, the number of days from the forecast date to the fiscal quarter-end (*HORIZON*) has a large median than mean. The 25th percentile is negative, which indicates that a significant number of analysts release their forecasts after fiscal quarter end, but before earnings are announced. All variables are winsorized at the 1% and 99%.

Table 2 finds that analysts' forecast accuracy (relative to peer analysts who follow the same firm) is positively related to the size of the broker and the frequency of forecasts. We find that the experience related variables (*FIRMEXP and GENEXP*) are significantly and positively related with forecast accuracy (*ACC)*. This means that the analysts' forecast accuracy improves as the analysts gain more experience. The forecast accuracy is also negatively related to the number of firms and industries followed, and the forecast horizon.

Some variables are highly correlated to each other, raising the possibility of multicollinearity. For example, the forecast frequency has a correlation of -0.4833 with the forecast horizon. Since our sample is based on the last forecast, this is intuitive. As an analyst makes more quarterly forecasts, the average number of days between the last forecast and the announcement date falls. Also, the number of firms that an analyst follows is highly correlated with both the number of industries that an analyst follows and an analyst's general level of experience. The correlations are 0.3728 and 0.1971, respectively.

Finally, the general experience and the firm-specific experience are positively correlated at 0.5908. To control for the possibility of multicollinearity, we run the tests with both and only one of each potentially problematic set of variables. Untabulated results of the coefficients across these regressions are generally consistent, indicating that multicollinearity is not a problem.

4.2 Univariate result

In this section, we compare the mean of analysts' forecast accuracy (*ACC*) between analysts who change coverage and their peer analysts.

4.2.1 Comparison of forecast accuracy

Table 3 examines how analysts' adding and dropping coverage is associated their forecast accuracy.

Panel A tabulates the mean forecast accuracy and the difference in mean forecast accuracy between analysts who add coverage of a firm (ADD_{ijt} = 1) and their peer analysts who have been following the same firm (ADD_{ijt} = 0). Panel B tabulates the mean forecast accuracy and the difference in mean forecast accuracy between analysts who drop coverage of a firm ($DROP_{ijt}$ = 1) and the remaining peer analysts who follow the same firm ($DROP_{ijt}$ = 0).

The mean forecast accuracy, the difference in mean forecast accuracy, and t-statistics reported in this table are based on the Fama-MacBeth (1973) procedure: Compute the mean accuracy each quarter, and report the time-series mean over the sample period (322 quarters).

For the analysts' adding coverage of a firm, Panel A finds that the mean forecast accuracy for analysts who start following a firm is significantly lower (0.578) than that of forecast accuracy for analysts who follow the same firm (0.600). This means that the forecast accuracy of analysts who just add to cover a firm is lower than that of peer analysts who have already following the same firm. On average, it seems that when analysts add coverage of a firm, their forecast accuracy is mitigated, possibly due to their lack of firm-specific experience.

Turning to analysts' dropping coverage of a firm, Panel B finds that when analysts stop following a firm, the mean forecast accuracy for the analysts is 0.525, which is significantly lower than the forecast accuracy of their peer analysts who follow the firm (0.612). This suggests that when analysts drop coverage of a firm, the analysts seem to make less effort to issue their forecasts, resulting in issuing less accurate forecasts than their peers.

4.3 Regression result

In this section, we reports the results of the estimating regression model that explains the analysts' forecast accuracy when the analyst add (drop) coverage of a firm using analyst characteristics.

However, our time series regression can spuriously show inter-temporal persistence over the years, simply due to analysts' time invariant characteristics. On top of it, our panel data is susceptible to special events and unexpected variation, which can affect the analyst's forecast behavior. Furthermore, we might get correlated errors analyst-year level because it is possible that analysts keep changing coverage of firms in their early career due to their career concerns.

To address these issues, we employ a regression model with year fixed and analyst fixed effects. Specifically, in tables 4, 5, 6, and 7, Model (1) reports the results based without considering fixed effects, models (2) and (3) report the results with adjusting year fixed effect, and the results with adjusting both year and analyst fixed effects, respectively.

4.3.1 Regression of forecast accuracy of analysts who add coverage of a firm on analysts' characteristics

Table 4 investigates our hypothesis 1a whether the analysts' adding coverage of a firm is associated with the analysts' forecast accuracy, relative to the peer analysts who follow the same firm, after controlling the factors known to affect forecast accuracy.

Table 3 documents that when an analyst adds coverage of a firm, the forecast accuracy of the analyst for the firm is lower relative to the peer analysts who have been following the same firm.

However, it is not clear whether the lower forecast accuracy of analysts who add coverage of a firm relative to their peer analysts, is driven by the individual analyst's characteristics that we did not consider. For instance, relatively less experienced analysts than peer analysts can issue less accurate forecasts when they add coverage of a firm. Analysts employed by relatively smaller broker than peer analysts can be less accurate due to limited available resources in the broker. In addition, the forecast accuracy of the analysts might be mitigated due to their high workload if they follow more industries/firms than their peers.

To address the issues, we regress the analysts' forecast accuracy after controlling for individual analyst's characteristics. We also include a dummy variable ADD_{ijt}, to measure the average effect of analysts who add coverage of firms on forecast accuracy.

To see whether the results from our analyses are sensitive to the adjustment of fixed effects, we provide the results from the fixed effect regression models. More specifically, in Table 4, model (1) reports the results without considering fixed effects, model (2) reports the results with adjusting year fixed effect, and model (3) reports the results with adjusting both year and analyst fixed effects.

Table 4 finds that analysts' forecast accuracy of the firm that they add coverage is significantly lower relative to their peer analysts (The coefficient on *ADD* is -0.0316, Model (3) in Table 4) after controlling for the factors known to affect analysts' forecast accuracy. Specifically, the coefficient on *ADD* is -0.0418, -0.0410, -0.0316, from Models (1), (2), and (3), respectively in Table 4, suggesting that the result is robust regardless of the three regression models after controlling for analyst and year fixed effects. Also, our result is the consistent with the univariate result that analysts who add coverage of a firm issue less accurate forecasts relative to their peer analysts covering the same firm.

As for results of the control variables in the regression models, they are generally consistent with the previous literature. Specifically, analysts' high workload (captured by the coefficient on *NFIRM* and *INDUSTRY*) seems to diminish the analysts' forecast accuracy. The positive coefficient on *HORIZON* implies that as it approaches to forecast period end, the forecast accuracy increases.

One noticeable finding in our result is that analysts' forecast accuracy does not increase, as analysts are more experienced (captured by *FIRMEXP* and *GENEXP*) and the coefficient on *GENEXP* is only significant in model (3). It is possibly because our analysis includes the firm-quarter observations only when analysts change their coverage. In other words, we do not consider the firm-quarter observations if no analysts make coverage changes. Hence, due to the sample construction, our sample inevitably represents more observations from less experienced analysts who add coverage of a firm.

Also, the coefficient on *BROKERSIZE* flips signs across the three models and therefore, it is only partially consistent with the prior literature that resources available to the analysts employed large brokerage houses help them issue more accurate EPS forecasts relative to their peer analysts. This finding may be driven by the situation in which by controlling both year and analyst fixed effects, we are additionally able to control year-analyst effects that persist in our sample such as the observations with little variations in size of brokerage firms over the years.

4.3.2 Regression of forecast accuracy of rookie analysts on analysts' characteristics

Table 5 tests hypothesis 1b to investigate whether rookie analysts' adding coverage of a firm is associated with the analysts' forecast accuracy, relative to the existing peer analysts, after controlling the factors known to affect forecast accuracy.

The univariate result in Panel A of Table 3 shows that the forecast accuracy from the analysts who add coverage of a firm is lower relative to that of the peer analysts following the same firm. Also, the result in Table 4 rules out the possibility that the lower forecast accuracy of analysts who add coverage is driven by the individual analyst's characteristics such as the broker size, experience, and high workload.

However, it is still not clear whether the low forecast accuracy of the analysts who add coverage of a firm is due to the less-experienced rookie analysts being more likely to issue less accurate forecasts.

To address this issue, we regress analysts' forecast accuracy after controlling for individual analyst's characteristics. Also, we include dummy variables, $ROOKIE_{it}$ and ADD_{ijt}*$ROOKIE_{it}$. See 3.3 Empirical models for detailed definition.

Table 5 reports the results of estimating regression model after controlling for year and analyst fixed effects. Model (1) is based on the results without considering fixed effects. Models (2) and (3) are based on the results with adjusting year fixed effect and both year and analyst fixed effects, respectively.

The coefficients on ADD_{ijt} in our models (1), (2), and (3) are all negative and significant, suggesting that the forecast accuracy of the analysts who add coverage of a firm is lower relative to their peers who have been following the firm. Also, the coefficient on $ROOKIE_{it}$ is also significantly negative across three models (1), (2), and (3) and it implies that the forecast accuracy of rookie analysts is lower relative to experienced analysts. The coefficient on the interaction term on ADD_{ijt}*$ROOKIE_{it}$, is significantly positive, while we find the significantly negative coefficient on $ROOKIE_{it}$.

We interpret the results in Table 5 that when analysts add coverage of a firm or the analysts are rookie with limited general experience, their forecast accuracy is lower relative to their peers. On the contrary, rookies seem to make an extra effort to research the added firm and end up issuing more accurate forecasts than peers, documented by the positive significant interaction coefficient on ADD_{ijt}*$ROOKIE_{it}$. Also, the rookie analysts do not dominate our results since the coefficient on ADD_{ijt}*$ROOKIE_{it}$ is positive and the coefficient on ADD_{ijt} is negative in Model (3) of Table 5 (0.0197 vs. -0.0349).

Turning to control variables, as in Table 4, the coefficient on *BROKERSIZE* changes the sign in Model (3) and it is significantly negative. The coefficient on *GENEXP* is only significant under model (3) only. The rest of the control variables are consistent with the prior research.

4.3.3 Regression of forecast accuracy of analysts who drop coverage of a firm on analysts' characteristics

Table 6 investigates the hypothesis 2a whether the analysts' dropping coverage of a firm is associated with the analyst EPS forecast accuracy, relative to the peer analysts who follow the same firm, after controlling the factors known to affect the forecast accuracy.

Panel B of Table 3 documents that when an analyst drops coverage of a firm, the forecast accuracy for the firm is lower relative to the remaining peer analysts. However, it is not clear whether the lower forecast accuracy relative to his peers is driven by the individual analyst's characteristics that we fail to control. For example, if an analyst's workload is heavier than his peers (proxied by the number of firms/industries that he follows), this might explain why his forecast accuracy is lower than other analysts. Also, if the timing when he issues his EPS forecasts is earlier than his peers, it can be associated with his forecast accuracy negatively. Considering that analyst's prior forecast accuracy does not change over a short period of time, an analyst's previous lower forecast accuracy of a firm also can explain why an analyst have lower forecast accuracy than peers this quarter.

To address the issue, we regress analysts' forecast accuracy after controlling for individual analyst's characteristics. We also include a dummy variable, $DROP_{ijt}$, to measure the average effect of analysts' dropping coverage of a firm on their forecast accuracy. Whereas we do not consider fixed effect in Model (1), Models (2), and (3) do adjust year fixed effect and both year and analyst fixed effects, respectively.

Table 6 finds that analysts' forecast accuracy of the dropped firm is significantly negative (The coefficient on $DROP_{ijt}$ is -0.0437, Model (3) in Table 6) after controlling the factors known to affect analysts' forecast accuracy. This result is robust regardless of the regressions after controlling analyst and year fixed effects (The coefficient on $DROP_{ijt}$ is -0.0537, Models (2) and (3) in Table 6). Also, this is the consistent with the univariate result that the forecast accuracy of analysts who drop coverage of a firm is lower than the remaining peer analysts. The result in Table 6 suggests that analysts' intention not to continue issuing forecast for a firm can discourage them from spending much time on the firm, resulting in low forecast accuracy.

As for control variables, analysts' forecast accuracy in prior quarter is positively associated with current period forecast accuracy. It implies that forecast accuracy does not dramatically change over one quarter. The results of other control variables except for *BROKERSIZE*, *FIRMEXP*, and *GENEXP* are the qualitatively the same with the previous results.

Specifically, the significantly positive coefficient on *BROKERSIZE* become not significant once we adjust year and analyst fixed effects. It is possible that we adjust the situation in which there is no pronounced inter-temporal difference in broker size between years and therefore the size of broker does not have significant effect on analysts forecast accuracy. Also, the coefficient on *FIRMEXP* is not significant across all three models. The coefficient on *GENEXP* for Models (3) is significantly negative. Also, there is a possibility that our sample construction process that includes firm-quarter observations, when analysts drop coverage of a firm, probably drives these results.

4.3.4 Regression of forecast accuracy of retiring analysts who drop coverage of a firm on analysts' characteristics

Table 7 tests hypothesis 2b to investigate whether retiring analysts' (equivalently, analysts who leave the I/B/E/S sample permanently) dropping coverage is associated with analysts' forecast accuracy, relative to the remaining peer analysts, after controlling the factors known to affect forecast accuracy.

The univariate result in Panel B of Table 3 shows that the forecast accuracy of analysts who drop coverage of a firm is lower relative to that of remaining peer analysts. Also, the result in Table 6 documents that the result is not driven by the individual analyst's characteristic such as the broker size, experience, and workload.

However, we cannot rule out the possibility that the result is due to the retiring analysts being more likely to issue the less accurate forecasts. For example, retiring analysts can be the analysts who drop coverage of a firm and stop analyst career due to their low forecast accuracy relative to their peer analysts.

To address this alternative hypothesis, we regress analysts' forecast accuracy after controlling for individual analyst's characteristics. Also, we include dummy variables, $RETIRE_{it}$ and $DROP_{ijt}*RETIRE_{it}$. See 3.3 Empirical models for detailed definition.

Table 7 reports the result of estimating regression model after controlling analyst and year fixed effects. Model (1) does not consider any fixed effects. Model (2) considers year fixed effect only and Model (3) considers both year and analyst fixed effects. The coefficients on $DROP_{ijt}$ in our models (1), (2), and (3) are all negative and significant, suggesting that the forecast accuracy of the analysts who drop coverage of a firm is lower relative to the remaining peers. Also, the coefficient on $RETIRE_{it}$ is also significantly negative and it implies that the forecast accuracy of retiring analysts is lower relative to the remaining peer analysts. The interaction coefficient on $DROP_{ijt}*RETIRE_{it}$ is significantly positive, while we find the significantly negative coefficient on $RETIRE_{it}$.

We interpret the results in Table 7 that, the accuracy of analyst' forecasts differs, depending on whether they plan to continue to work as an analyst. However, the accuracy of very last forecast of firms from retiring analysts, on average, is significantly higher relative to the remaining analysts.

It seems to capture the situation in which the retiring analysts might not necessarily be the analysts who are fired due to their inferior forecasting ability. But, they are the analysts who reach the normal retirement age or resign voluntary. Under the circumstances, it is more likely that retiring analysts would perform their forecast activity diligently, not resulting in issuing less accurate forecast than peers.

More importantly, retiring analysts do not dominate our results considering that the coefficient on $DROP_{ijt}*RETIRE_{it}$ is positive impact on forecast accuracy and the coefficient on $DROP_{ijt}$ is negative impact on forecast accuracy (0.0104 vs. -0.0457) in Model (3) of Table 7.

As for control variables, they are qualitatively the same with the results documented on Table 6. The coefficient on *BROKERSIZE* is not significant and *FIRMEXP* and *GENEXP* flip the signs and significances.

5. Further analysis

In this section, we perform further analyses to examine whether analysts' industry expertise is associated with the forecast accuracy of analysts who add coverage of a firm compared to the peer analysts.

5.1 Primary industry

Table 8 investigates whether there is a difference in analysts' forecast accuracy between the analysts who add coverage of a firm that is not within their primary industry and the analysts who are already following the firm.

Table 4 finds that analysts' forecast accuracy of a firm that they add coverage is significantly less accurate than their peers. Table 5 suggests that the rookie analysts seem to expend an extra effort to research the firms that they add coverage and end up issuing more accurate forecasts than their peers.

Even though we regress forecast accuracy after controlling for individual analyst's characteristics, it is still possible that our result is from the analysts' adding coverage of a firm where its earnings is difficult to predict. However, it is not easy to empirically determine the level of difficulty to predict earnings since the level of difficulty may be different depending on individual analyst's perception.

To address the issue, first, we assume that an analyst's primary industry would be the area in which she is familiar and therefore, would be more accurate in predicting earnings. Then, we regress analysts' forecast accuracy after controlling for individual analyst's characteristics and employing dummy and interaction variables, $NPRIM\_IND_{it}$, ADD_{ijt}, and $ADD_{ijt}*NPRIM\_IND_{it}$. Specifically, we define the dummy variable $NPRIM\_IND_{it}$ as 1 when analyst *i* follows a firm within her non-primary industries (zero otherwise). Primary industry is analyst *i*'s most frequently following industry (based on two-digit SIC code) in a year *t*. We define an interaction term, $ADD_{ijt}*NPRIM\_IND_{it}$, which captures whether the forecast accuracy of an analyst who adds coverage of a firm depends on his industry expertise.

We construct the regression model following Clement (1999), Jacob, Lys, and Neale (1999), and Clement and Tse (2005) to see the effects of analysts' coverage change on analyst forecast accuracy after controlling individual analyst's characteristics. Since our emphasis is on the forecast accuracy of analysts who add coverage of a firm that is not within their primary industry rather than that of all analysts who follow the firm, we add dummy and interaction variables, $NPRIM\_IND_{it}$, ADD_{ijt}, and $ADD_{ijt}*NPRIM\_IND_{it}$ to the existing model.

Also, to see whether the results from our regression model is susceptible to the control of year and analyst fixed effects, we construct three models: (1) no adjustment on fixed effect, (2) adjustment on year fixed effect, and (3) adjustment on year and analyst fixed effects. We use the following regression model to test.

We use the following regression model to test.

$$ACC_{ijt} = \beta_0 + \beta_1 ADD_{ijt} + \beta_2 NPRIM\_IND_{it} + \beta_3 ADD*NPRIM\_IND_{it} + \beta_4 FREQUENCY_{ijt} + \beta_5 BROKERSIZE_{ijt} + \beta_6 NFIRM_{ijt} + \beta_7 INDUSTRY_{ijt} + \beta_8 FIRMEXP_{ijt} + \beta_9 GENEXP_{ijt} + \beta_{10} HORIZON_{ijt} + \varepsilon_{ijt}$$

Table 8 shows the result of estimating regression of the forecast accuracy from the analysts who add coverage of a firm that is not within their primary industry. Consistent with the previous results, the overall average effect on forecast accuracy of analysts who add coverage of a firm (ADD_{ijt}) is negative across all models (-0.0458, -0.0460, and -0.0404, Models (1), (2), and 0.0404, Model (3) in Table 8). When an analyst adds coverage of a firm that is not within their primary industry, the overall average effect on accuracy ($NPRIM\_IND_{it}$) is negative (-0.0112), which supports our assumption that analysts feel less familiar with the firms if they do not have an industry expertise. The coefficient on $ADD_{ijt}*NPRIM\_IND_{it}$ is significantly positive.

We interpret the results in Table 8 that an analyst is more accurate when forecasting a firm from their primary industry. However, when analysts add coverage of a firm that is not within their primary industry, our results suggest that analysts tend to pay more attention to the newly added firm to compensate for their non-proficiency of the industry knowledge and issue more accurate forecasts than their peers.

Also, the forecast accuracy of analysts who add coverage of a firm that is not within their primary industry do not dominate our results since the coefficient on $ADD_{ijt}*NPRIM\_IND_{it}$ is positively related to forecast accuracy and the coefficient on ADD_{ijt} is negatively related to forecast accuracy (0.0142 vs. -0.0404) in Model (3) of Table 8.

Turning to control variables, as documented in Tables 4 and 5, the coefficients on B*ROKERSIZE*, *FIRMEXP*, and *GENEXP* are not consistent with the prior literature. The coefficient on B*ROKERSIZE* changes the sign after adjusting both year and analyst fixed effect (Model (3)). Analysts' general or firm related experience is significantly inversely related to analysts' forecast accuracy across three models.

6. Conclusion

This paper revisits the conflicting results in prior research, and examine whether analysts' forecast accuracy is higher or lower when an analyst adds or drops coverage.

We find that when analysts add coverage for a firm, their forecast accuracy is significantly lower relative to their peers who follow the same firm. We examine the alternative hypothesis that our finding is driven by rookie analysts (analysts with less than one-year experience) being more likely to issue less accurate forecasts. While the forecast accuracy of rookies is lower relative to that of experienced analysts, their forecast accuracy is higher relative to their peers when adding coverage (consistent with making a good "first impression").

When analysts drop coverage for a firm, their forecast accuracy (based on their last forecast) is also significantly lower relative to that of their peer analysts. We explore the possibility that our finding arises from retiring analysts (i.e., analysts who are within their final year before retiring). While the forecast accuracy for retiring analysts is significantly lower relative to those who are not retiring, we find that their forecasts for dropped firms (i.e., final forecast) are more accurate relative to their peers (consistent with leaving a good "final legacy"). This suggests that analysts put in extra effort for their final analysts' report.

Finally, we investigate the impact of industry expertise on their forecast accuracy. We consider the case in which analysts add coverage of a firm that is not within their primary industry. We find analysts' forecast to be less accurate for firms that are not within their primary industry. However, when analysts add coverage of a firm from their non-primary industries, our results suggest that analysts tend to pay more attention to the newly added firm to make up for their limited industry knowledge, resulting in more accurate forecasts relative to their peers.

In conclusion, this study seeks to understand the accuracy of forecasts when an analyst add or drop coverage for a firm. Our results indicate that forecast accuracy is significantly lower in both cases, relative to their peer analysts who follow the same firm. Our results is not driven by rookies nor retiring analysts.

References

Brown, L. D. (1993). Earnings forecasting research: Its implications for capital markets research. *International Journal of Forecasting*, 9(3), 295-320.

Brown, L. D. (2001). How important is past analyst forecast accuracy? *Financial Analysts Journal*:44-49.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2015). Inside the "Black Box" of Sell-Side Financial Analysts. Journal of Accounting Research, 53(1), 1-47.

Cheong, F. S., & Thomas, J. (2011). Why do EPS forecast error and dispersion not vary with scale? Implications for analyst and managerial behavior. *Journal of Accounting Research*, 49(2), 359-401.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27 (3):285-303.

Clement, M. B., and S. Y. Tse. (2005). Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance* 60 (1):307-341.

Emery, D. R., and X. Li. (2009). Are the Wall Street analyst rankings popularity contests? *Journal of Financial and Quantitative Analysis* 44 (2):411-437.

Hong, H., J. D. Kubik, and A. Solomon. (2000). Security analysts' career concerns and herding of earnings forecasts. *The Rand Journal of Economics* 31 (1):121-144.

Jacob, J., T. Z. Lys, and M. A. Neale. (1999). Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics* 28 (1):51-82.

Li, Y., R. Rau, and J. Xu. (2009). The Five Stages of Analyst Careers: Coverage C hoices and Changing Influence. Available at SSRN: http://ssrn.com/abstract=14603 82. Last Accessed May 7, 2015.

McNichols, M., and P. C. O'Brien. (1997). Self-selection and analyst coverage. *Journal of Accounting Research* 35:167-199.

Mikhail, M. B., B. R. Walther, and R. H. Willis. (1999). Does Forecast Accuracy Matter to Security Analysts? *The Accounting Review* 74 (2):185-200.

———. (2003). The effect of experience on security analyst underreaction. *Journal of Accounting and Economics* 35 (1):101-116.

Ramnath, S., Rock, S., & Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24(1), 34-75.

Schutte, M., & Unlu, E. (2009). Do security analysts reduce noise?. *Financial Analysts Journal*, *65*(3), 40-54.

Sinha, P., Brown, L. D., & Das, S. (1997). A Re-Examination of Financial Analysts' Differential Earnings Forecast Accuracy. *Contemporary Accounting Research*, *14*(1), 1-42.

Stickel, S. E. (1992). Reputation and performance among security analysts. *Journal of Finance*:1811-1836.

Stickel, S. E. (1993). Accuracy improvements from a consensus of updated individual analyst earnings forecasts. *International Journal of Forecasting*, 9(3), 345-353.

Sun, J. (2009). Governance role of analyst coverage and investor protection. *Financial Analysts Journal*, *65*(6), 52-64.

Yu, F. F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics*, *88*(2), 245-271.

Table 1
Sample selection and descriptive statistics

Panel A: Sample selection by year and coverage change, separately for coverage added and dropped.

Coverage	[Added]			[Dropped]		
Year	Sample	Matched	Sample + Matched	Sample	Matched	Sample + Matched
1985	219	500	719	54	342	396
1986	454	1,079	1,533	152	762	914
1987	2,663	7,883	10,546	1,253	5,945	7,198
1988	3,336	11,118	14,454	1,364	7,510	8,874
1989	3,718	12,999	16,717	3,027	11,003	14,030
1990	3,046	12,289	15,335	1,306	8,516	9,822
1991	2,215	11,628	13,843	967	7,274	8,241
1992	1,839	10,976	12,815	1,416	10,181	11,597
1993	2,849	12,527	15,376	1,743	10,597	12,340
1994	3,794	18,682	22,476	2,695	15,933	18,628
1995	3,670	18,152	21,822	2,860	15,744	18,604
1996	3,775	17,114	20,889	2,728	15,077	17,805
1997	4,259	19,177	23,436	2,987	15,801	18,788
1998	4,645	21,701	26,346	3,391	18,076	21,467
1999	5,648	25,301	30,949	4,209	20,106	24,315
2000	5,041	23,179	28,220	4,456	20,993	25,449
2001	7,011	31,290	38,301	4,860	26,082	30,942
2002	6,328	30,631	36,959	4,931	25,931	30,862
2003	5,646	31,073	36,719	3,668	25,119	28,787
2004	5,461	33,447	38,908	3,829	27,253	31,082
2005	5,598	33,799	39,397	4,223	29,619	33,842
2006	5,797	35,786	41,583	4,458	30,335	34,793
2007	5,462	34,446	39,908	4,990	33,251	38,241
2008	5,470	35,488	40,958	5,446	34,288	39,734
2009	5,827	40,274	46,101	3,218	26,991	30,209
2010	5,340	41,906	47,246	3,596	32,308	35,904
2011	5,448	43,057	48,505	4,794	39,390	44,184
2012	5,247	41,790	47,037	4,693	39,506	44,199
Total	119,806	657,292	777,098	87,314	553,933	641,247

Panel B: Descriptive statistics

Variables (before normalizing to range between zero and one)	Mean	25th Percentile	Median	75th Percentile
BROKERSIZE: Number of analysts employed in broker	58.0	22	49	90
FREQUENCY: Number of forecasts issued by an analyst for a firm-quarter	1.5	1	1	2
NFIRM: Number of firms that an analyst follows	16.9	11	16	21
INDUSTRY: Number of industries that an analyst follows	3.4	2	3	5
HORIZON: Number of Days to fiscal quarter-end	24.7	-7	23	57
GENEXP: Years of general experience	6.4	2	5	9
FIRMEXP: Years of firm-specific experience	3.0	1	2	4

This Table provides the sample selection and descriptive statistics. Panel A reports the sample selection by year and coverage change, separately for coverage added and dropped. Panel B reports the descriptive statistics that show the distribution of raw analyst characteristics.

Table 2
Pearson correlation among forecasts and analyst characteristics

	ACC	*BROKERSIZE*	*FREQUENCY*	*NFIRM*	*INDUSTRY*	*HORIZON*	*GENEXP*	*FIRMEXP*
ACC	1							
BROKERSIZE	0.0181 (<.0001)	1						
FREQUENCY	0.1183 (<.0001)	0.0669 (<.0001)	1					
NFIRM	-0.0091 (<.0001)	0.0229 (<.0001)	0.0297 (<.0001)	1				
INDUSTRY	-0.0268 (<.0001)	-0.0827 (<.0001)	-0.0214 (<.0001)	0.3728 (<.0001)	1			
HORIZON	-0.1371 (<.0001)	0.0096 (<.0001)	-0.4833 (<.0001)	-0.0119 (<.0001)	0.0228 (<.0001)	1		
GENEXP	0.0060 (<.0001)	0.0824 (<.0001)	0.0459 (<.0001)	0.1971 (<.0001)	0.1209 (<.0001)	0.0273 (<.0001)	1	
FIRMEXP	0.0222 (<.0001)	0.0825 (<.0001)	0.0830 (<.0001)	0.1209 (<.0001)	0.0424 (<.0001)	0.0276 (<.0001)	0.5908 (<.0001)	1

This Table reports the Pearson correlations among analyst characteristics. To measure analyst's EPS forecast accuracy, we first define AFE_{ijt} as the absolute forecast error of analyst *i* for firm *j* in quarter *t* (= |forecasted EPS – actual EPS|). We report correlation coefficients based on raw values of $BROKERSIZE_{ijt}$, $FREQUENCY_{ijt}$, $NFIRM_{ijt}$, $INDUSTRY_{ijt}$, $GENEXP_{ijt}$, $FIRMEXP_{ijt}$, and ACC_{ijt} (scaled) to see how analysts' individual characteristics affect the (firm effect controlled) forecast accuracy. Following Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy. We scale forecast accuracy (*ACC*) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error. All other variables are defined in Table 1.

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

Table 3
Comparison of Forecast Accuracy

Panel A: Comparison of forecast accuracy between analysts who add coverage of a firm and existing peer analysts who follow the same firm

Variable	Mean forecast accuracy	t - value
Added *(ADD* = 1*)*	0.578	184.03
Existing *(ADD* = 0*)*	0.600	305.23
Difference	-0.022	-7.21

Panel B: Comparison of forecast accuracy between analysts who drop coverage of a firm and remaining peer analysts.

Variable	Mean forecast accuracy	t - value
Dropped (*DROP* = 1)	0.525	162.52
Remaining (*DROP* = 0)	0.612	273.27
Difference	-0.089	-22.73

This Table examines how analysts' adding and dropping coverage is associated with their EPS forecast accuracy. Panel A tabulates the mean forecast accuracy and the difference in mean forecast accuracy between analysts who add coverage of a firm (*ADD* = 1) and their peer analysts who have been following the same firm (*ADD* = 0). Panel B tabulates the mean forecast accuracy and the difference in mean forecast accuracy between analysts who drop coverage of a firm (*DROP* = 1) and the remaining peer analysts who follow the same firm (*DROP* = 0). Following Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy. We scale forecast accuracy (*ACC*) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error.

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

The mean forecast accuracy, the difference in mean forecast accuracy, and t-statistics reported in this table are based on the Fama-MacBeth (1973) procedure: Compute the mean accuracy each quarter, and report the time-series mean over the sample period (322 quarters). *, **, and *** denote significance at the 10, 5, and 1 percent significance levels, respectively.

Table 4
Regression of forecast accuracy of analysts who add coverage of a firm on analysts' characteristics

$$ACC_{ijt} = \beta_0 + \beta_1 ADD_{ijt} + \beta_2 FREQUENCY_{ijt} + \beta_3 BROKERSIZE_{ijt} + \beta_4 NFIRM_{ijt} + \beta_5 INDUSTRY_{ijt} + \beta_6 FIRMEXP_{ijt} + \beta_7 GENEXP_{ijt} + \beta_8 HORIZON_{ijt} + \varepsilon_{ijt}$$

VARIABLES	Model (1)	Model (2)	Model (3)
CONSTANT	0.6803***	0.6804***	0.6666***
	(523.07)	(522.74)	(42.41)
ADD	-0.0418***	-0.0410***	-0.0316***
	(-34.07)	(-33.24)	(-24.59)
FREQUENCY	0.0238***	0.0225***	0.0189***
	(20.67)	(19.56)	(15.89)
BROKERSIZE	0.0065***	0.0068***	-0.0070***
	(5.46)	(5.68)	(-3.31)
NFIRM	-0.0049***	-0.0059***	-0.0077***
	(-3.40)	(-4.05)	(-4.10)
INDUSTRY	-0.0174***	-0.0174***	-0.0095***
	(-13.51)	(-13.51)	(-5.66)
FIRMEXP	-0.0093***	-0.0089***	-0.0100***
	(-6.76)	(-6.49)	(-6.81)
GENEXP	-0.0009	0.0018	-0.0246***
	(-0.62)	(1.31)	(-8.90)
HORIZON	-0.1328***	-0.1343***	-0.1386***
	(-116.74)	(-117.27)	(-115.04)
Observations	777,098	777,098	777,098
R-squared	0.028	0.028	0.027
Year Fixed Effect	NO	YES	YES
Analyst Fixed Effect	NO	NO	YES

This table investigates our hypothesis 1a whether the analysts' adding coverage of a firm is associated with the analysts' EPS forecast accuracy, compared to the peer analysts who follow the same firm, after controlling the factors known to affect forecast accuracy. The value of ADD_{ijt} is 1 if analyst *i* starts to follow firm *j* in each quarter *t* (zero otherwise). $BROKERSIZE_{ijt}$ is the size of broker employing analyst *i* who follows firm *j* in quarter *t*. $FREQUENCY_{ijt}$ is the number of analyst *i*'s forecasts for firm *j* in quarter *t*. $NFIRM_{ijt}$ is the number of followed firms by analyst *i* who follows firm *j* in year *t*. $INDUSTRY_{ijt}$ is the number of followed industries (two-digit SICs) by analyst *i* who follows firm *j* in year *t*. $HORIZON_{ijt}$ is the number of days from forecast issuance date of firm *j* to firm's fiscal quarter *t* by analyst *i*. $GENEXP_{ijt}$ is the overall years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. $FIRMEXP_{ijt}$ is the firm-related years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. Consistent with Clement and Tse (2005, p.314), all variables are scaled to range from zero to one:

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\ min_{jt}}{Raw\_Characteristic\ max_{jt} - Raw\_Characteristic\ min_{jt}}$$

where *Raw_Characteristic* $\min_{jt}$ and *Raw_Characteristic* $\max_{jt}$ are minimum (maximum) raw characteristics across all analysts following firm *j* in quarter *t*.

Similarly, following Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy:

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

We scale forecast accuracy (*ACC*) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error. The *t*-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent significance levels, respectively.

Table 5
Regression of forecast accuracy of rookie analysts who add coverage of a firm on analysts' characteristics

$$ACC_{ijt} = \beta_0 + \beta_1 ADD_{ijt} + \beta_2 ROOKIE_{it} + \beta_3 ADD_{ijt} * ROOKIE_{it} + \beta_4 FREQUENCY_{ijt} + \beta_5 BROKERSIZE_{ijt} + \beta_6 NFIRM_{ijt} + \beta_7 INDUSTRY_{ijt} + \beta_8 FIRMEXP_{ijt} + \beta_9 GENEXP_{ijt} + \beta_{10} HORIZON_{ijt} + \varepsilon_{ijt}$$

VARIABLES	Model (1)	Model (2)	Model (3)
CONSTANT	0.6821***	0.6819***	0.6671***
	(512.79)	(512.34)	(42.39)
ADD	-0.0430***	-0.0424***	-0.0349***
	(-30.90)	(-30.42)	(-24.43)
ROOKIE	-0.0188***	-0.0167***	-0.0091***
	(-6.96)	(-6.17)	(-3.04)
*ADD * ROOKIE*	0.0182***	0.0175***	0.0197***
	(5.27)	(5.05)	(5.49)
FREQUENCY	0.0238***	0.0226***	0.0189***
	(20.69)	(19.60)	(15.92)
BROKERSIZE	0.0064***	0.0067***	-0.0069***
	(5.41)	(5.65)	(-3.27)
NFIRM	-0.0054***	-0.0063***	-0.0075***
	(-3.75)	(-4.30)	(-3.97)
INDUSTRY	-0.0174***	-0.0174***	-0.0093***
	(-13.57)	(-13.56)	(-5.58)
FIRMEXP	-0.0105***	-0.0101***	-0.0112***
	(-7.57)	(-7.26)	(-7.52)
GENEXP	-0.0020	0.0009	-0.0241***
	(-1.43)	(0.61)	(-8.70)
HORIZON	-0.1326***	-0.1341***	-0.1386***
	(-116.58)	(-117.06)	(-114.98)
Observations	777,098	777,098	777,098
R-squared	0.028	0.028	0.027
Year Fixed Effect	NO	YES	YES
Analyst Fixed Effect	NO	NO	YES

This Table tests hypothesis 1b to investigate whether rookie analysts' adding coverage of a firm is associated with analysts' EPS forecast accuracy, considering the existing peer analysts, after controlling the factors known to affect forecast accuracy. The value of $ROOKIE_{it}$ is 1 if analyst *i* appears in the I/B/E/S for the first time (zero otherwise). The value of ADD_{ijt} is 1 if analyst *i* starts to follow firm *j* in each quarter *t* (zero otherwise). $ADD_{ijt}*ROOKIE_{it}$ is the interaction term. $BROKERSIZE_{ijt}$ is the size of broker employing analyst *i* who follows thefirm *j* in quarter *t*. $FREQUENCY_{ijt}$ is the number of analyst *i*'s forecasts for firm *j* in quarter *t*. $NFIRM_{ijt}$ is the number of followed firms by analyst *i* who follows firm *j* in year *t*. $INDUSTRY_{ijt}$ is the number of followed industries (two-digit SICs) by analyst *i* who follows firm *j* in year *t*. $HORIZON_{ijt}$ is the number of days from forecast issuance date of firm *j* to the firm's fiscal quarter *t* by analyst *i*. $GENEXP_{ijt}$ is the overall years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. $FIRMEXP_{ijt}$ is the firm-related years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. Consistent with Clement and Tse (2005, p.314), all variables are scaled to range from zero to one:

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\ min_{jt}}{Raw\_Characteristic\ max_{jt} - Raw\_Characteristic\ min_{jt}}$$

where *Raw_Characteristic* $\min_{jt}$ and *Raw_Characteristic* $\max_{jt}$ are minimum (maximum) raw characteristics across all analysts following firm *j* in quarter *t*.

Similarly, following Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy:

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

We scale forecast accuracy (*ACC*) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error. The *t*-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent significance levels, respectively.

Table 6
Regression of forecast accuracy of analysts who drop coverage of a firm on analysts' characteristics

$$ACC_{ijt} = \beta_0 + \beta_1 DROP_{ijt} + \beta_2 LAGACC_{ijt} + \beta_3 FREQUENCY_{ijt} + \beta_4 BROKERSIZE_{ijt} + \beta_5 NFIRM_{ijt} + \beta_6 INDUSTRY_{ijt} + \beta_7 FIRMEXP_{ijt} + \beta_8 GENEXP_{ijt} + \beta_9 HORIZON_{ijt} + \varepsilon_{ijt}$$

VARIABLES	Model (1)	Model (2)	Model (3)
CONSTANT	0.6372***	0.6385***	0.5966***
	(396.71)	(396.96)	(28.84)
DROP	-0.0547***	-0.0547***	-0.0437***
	(-44.07)	(-43.91)	(-32.20)
LAGACC	0.0743***	0.0734***	0.0542***
	(61.36)	(60.68)	(44.30)
FREQUENCY	0.0205***	0.0188***	0.0133***
	(15.93)	(14.54)	(9.88)
BROKERSIZE	0.0054***	0.0057***	-0.0043*
	(4.19)	(4.40)	(-1.83)
NFIRM	-0.0069***	-0.0078***	-0.0066***
	(-4.39)	(-4.95)	(-3.17)
INDUSTRY	-0.0143***	-0.0144***	-0.0085***
	(-10.24)	(-10.29)	(-4.62)
FIRMEXP	0.0012	0.0011	-0.0015
	(0.85)	(0.79)	(-0.98)
GENEXP	-0.0011	0.0020	-0.0210***
	(-0.71)	(1.30)	(-6.81)
HORIZON	-0.1268***	-0.1291***	-0.1383***
	(-99.94)	(-100.59)	(-101.42)
Observations	641,247	641,247	641,247
R-squared	0.039	0.039	0.034
Year Fixed Effect	NO	YES	YES
Analyst Fixed Effect	NO	NO	YES

This Table investigates the hypothesis 2a whether the analysts' dropping coverage of a firm is associated with analysts' EPS forecast accuracy, considering the peer analysts who follow the same firm, after controlling the factors known to affect the forecast accuracy. The value of $DROP_{ijt}$ is 1 if analyst *i* stops following a firm at quarter *t+1* (zero otherwise). $BROKERSIZE_{ijt}$ is the size of broker employing analyst *i* who follows firm *j* in quarter *t*. $FREQUENCY_{ijt}$ is the number of analyst *i*'s forecasts for firm *j* in quarter *t*. $NFIRM_{ijt}$ is the number of followed firms by analyst *i* who follows firm *j* in year *t*. $INDUSTRY_{ijt}$ is the number of followed industries (two-digit SICs) by analyst *i* who follows firm *j* in year *t*. $HORIZON_{ijt}$ is the number of days from forecast issuance date of firm *j* to the firm's fiscal quarter *t* by analyst *i*. $GENEXP_{ijt}$ is the overall years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. $FIRMEXP_{ijt}$ is the firm-related years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. Consistent with Clement and Tse (2005, p.314), all variables are scaled to range from zero to one:

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\ min_{jt}}{Raw\_Characteristic\ max_{jt} - Raw\_Characteristic\ min_{jt}}$$

where *Raw_Characteristic* $\min_{jt}$ and *Raw_Characteristic* $\max_{jt}$ are minimum (maximum) raw characteristics across all analysts following firm *j* in quarter *t*.

Similarly, following Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy:

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

We scale forecast accuracy (*ACC*) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error. The *t*-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent significance levels, respectively.

Table 7
Regression of forecast accuracy of the retiring analysts who drop coverage of a firm on analysts' characteristics

$$ACC_{ijt} = \beta_0 + \beta_1 DROP_{ijt} + \beta_2 RETIRE_{it} + \beta_3 DROP_{ijt}{*}RETIRE_{it} + \beta_4 LAGACC_{ijt} + \beta_5 FREQUENCY_{ijt} + \beta_6 BROKERSIZE_{ijt} + \beta_7 NFIRM_{ijt} + \beta_8 INDUSTRY_{ijt} + \beta_9 FIRMEXP_{ijt} + \beta_{10} GENEXP_{ijt} + \beta_{11} HORIZON_{ijt} + \varepsilon_{ijt}$$

VARIABLES	Model (1)	Model (2)	Model (3)
CONSTANT	0.6377***	0.6391***	0.5966***
	(395.09)	(395.31)	(28.84)
DROP	-0.0554***	-0.0550***	-0.0457***
	(-35.56)	(-35.21)	(-27.95)
RETIRE	-0.0079***	-0.0098***	-0.0059**
	(-3.15)	(-3.92)	(-2.07)
*DROP * RETIRE*	0.0089***	0.0099***	0.0104***
	(2.59)	(2.90)	(2.93)
LAGACC	0.0743***	0.0734***	0.0542***
	(61.36)	(60.68)	(44.30)
FREQUENCY	0.0206***	0.0188***	0.0133***
	(15.93)	(14.53)	(9.88)
BROKERSIZE	0.0054***	0.0057***	-0.0042*
	(4.15)	(4.35)	(-1.80)
NFIRM	-0.0071***	-0.0081***	-0.0064***
	(-4.50)	(-5.14)	(-3.08)
INDUSTRY	-0.0143***	-0.0143***	-0.0084***
	(-10.22)	(-10.27)	(-4.58)
FIRMEXP	0.0012	0.0012	-0.0015
	(0.86)	(0.81)	(-0.97)
GENEXP	-0.0011	0.0020	-0.0210***
	(-0.74)	(1.27)	(-6.81)
HORIZON	-0.1269***	-0.1292***	-0.1385***
	(-99.98)	(-100.66)	(-101.45)
Observations	641,247	641,247	641,247
R-squared	0.039	0.039	0.034
Year Fixed Effect	NO	YES	YES
Analyst Fixed Effect	NO	NO	YES

This Table tests hypothesis 2b to investigate whether retiring analysts' (equivalently, analysts who leave the I/B/E/S sample permanently) dropping coverage is associated with analysts' EPS forecast accuracy, considering the remaining peer analysts, after controlling the factors known to affect forecast accuracy. The value of $RETIRE_{it}$ equals 1 if an analyst leaves the I/B/E/S permanently in the following quarter *t+1* (zero otherwise). The value of $DROP_{ijt}$ is 1 if analyst *i* stops following a firm at quarter *t+1* (zero otherwise). $DROP_{ijt}*RETIRE_{it}$ is the interaction term. $BROKERSIZE_{ijt}$ is the size of broker employing analyst *i* who follows firm *j* in quarter *t*. $FREQUENCY_{ijt}$ is the number of analyst *i*'s forecasts for firm *j* in quarter *t*. $NFIRM_{ijt}$ is the number of followed firms by analyst *i* who follows firm *j* in year *t*. $INDUSTRY_{ijt}$ is the number of followed industries (two-digit SICs) by analyst *i* who follows firm *j* in year *t*. $HORIZON_{ijt}$ is the number of days from forecast issuance date of firm *j* to the firm's fiscal quarter *t* by analyst *i*. $GENEXP_{ijt}$ is the overall years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. $FIRMEXP_{ijt}$ is the firm-related years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. Consistent with Clement and Tse (2005, p.314), all variables are scaled to range from zero to one:

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\ min_{jt}}{Raw\_Characteristic\ max_{jt} - Raw\_Characteristic\ min_{jt}}$$

where *Raw_Characteristic* $\min_{jt}$ and *Raw_Characteristic* $\max_{jt}$ are minimum (maximum) raw characteristics across all analysts following firm *j* in quarter *t*.

Similarly, following Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy:

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

We scale forecast accuracy (*ACC*) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error. The *t*-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent significance levels, respectively.

Table 8
Regression of forecast accuracy of analysts who add coverage of a firm that is not within their primary industry

$ACC_{ijt} = \beta_0 + \beta_1 ADD_{ijt} + \beta_2 NPRIM\_IND_{it} + \beta_3 ADD{*}NPRIM\_IND_{it} + \beta_4 FREQUENCY_{ijt} + \beta_5 BROKERSIZE_{ijt} + \beta_6 NFIRM_{ijt} + \beta_7 INDUSTRY_{ijt} + \beta_8 FIRMEXP_{ijt} + \beta_9 GENEXP_{ijt} + \beta_{10} HORIZON_{ijt} + \varepsilon_{ijt}$

VARIABLES	Model (1)	Model (2)	Model (3)
CONSTANT	0.6940***	0.6926***	0.6826***
	(472.75)	(462.53)	(43.07)
ADD	-0.0458***	-0.0460***	-0.0404***
	(-21.95)	(-22.03)	(-19.14)
NPRIM_IND	-0.0202***	-0.0182***	-0.0112***
	(-19.87)	(-16.41)	(-8.87)
*ADD * NPRIM_IND*	0.0108***	0.0108***	0.0142***
	(4.47)	(4.47)	(5.73)
FREQUENCY	0.0239***	0.0230***	0.0189***
	(20.75)	(19.97)	(15.96)
BROKERSIZE	0.0061***	0.0065***	-0.0069***
	(5.12)	(5.42)	(-3.27)
NFIRM	-0.0080***	-0.0082***	-0.0081***
	(-5.48)	(-5.64)	(-4.27)
INDUSTRY	-0.0159***	-0.0160***	-0.0094***
	(-12.32)	(-12.46)	(-5.59)
FIRMEXP	-0.0145***	-0.0138***	-0.0131***
	(-10.28)	(-9.74)	(-8.69)
GENEXP	-0.0094***	-0.0068***	-0.0261***
	(-6.39)	(-4.45)	(-9.36)
HORIZON	-0.1331***	-0.1339***	-0.1385***
	(-117.05)	(-116.85)	(-114.91)
Observations	777,098	777,098	777,098
R-squared	0.029	0.029	0.027
Year Fixed Effect	NO	YES	YES
Analyst Fixed Effect	NO	NO	YES

This Table investigates whether there is a difference in analysts' EPS forecast accuracy between the analysts who add coverage of a firm that is not within their primary industry and the analysts who are already following the firm. The value of *NPRIM_IND* is 1 if analyst *i* follows a firm *j* in each quarter *t*, not from their primary industry (zero otherwise). The value of ADD_{ijt} is 1 if analyst *i* starts to follow a firm *j* in each quarter t (zero otherwise). $ADD_{ijt}*NPRIM\_IND_{it}$, is the interaction term. $BROKERSIZE_{ijt}$ is the size of broker employing analyst *i* who follows firm *j* in quarter *t*. $FREQUENCY_{ijt}$ is the number of analyst *i*'s forecasts for firm *j* in quarter *t*. $NFIRM_{ijt}$ is the number of followed firms by analyst *i* who follows firm *j* in year *t*. $INDUSTRY_{ijt}$ is the number of followed industries (two-digit SICs) by analyst *i* who follows firm *j* in year *t*. $HORIZON_{ijt}$ is the number of days from forecast issuance date of firm *j* to the firm's fiscal quarter t by analyst *i*. $GENEXP_{ijt}$ is the overall years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. $FIRMEXP_{ijt}$ is the firm-related years of forecasting experience of analyst *i* who follows firm *j* in quarter *t*. Consistent with Clement and Tse (2005, p.314), all variables are scaled to range from zero to one:

$$Characteristic_{ijt} = \frac{Raw\_Characteristic_{ijt} - Raw\_Characteristic\ min_{jt}}{Raw\_Characteristic\ max_{jt} - Raw\_Characteristic\ min_{jt}}$$

where *Raw_Characteristic* $\min_{jt}$ and *Raw_Characteristic* $\max_{jt}$ are minimum (maximum) raw characteristics across all analysts following firm *j* in quarter *t*.

Similarly, following Clement and Tse (2005, p.315), forecast accuracy (*ACC*) is defined such that forecasts with lower absolute error are defined to have higher forecast accuracy:

$$ACC_{ijt} = \frac{AFE\ max_{jt} - AFE_{ijt}}{AFE\ max_{jt} - AFE\ min_{jt}}$$

We scale forecast accuracy (*ACC*) to range between zero and one, so that our results are less susceptible to extreme outliers. Otherwise, the mean forecast accuracy (when aggregated across firms) will be skewed towards the subset of samples with high absolute forecast error. The *t*-statistics are in parentheses. *, **, and *** denote significance at the 10, 5, and 1 percent significance levels, respectively.