Do Analysts Who Understand Accounting Conservatism Exhibit Better Forecasting Performance?

JAY HEON JUNG, *Cass Business School, City, University of London*
jay.jung@city.ac.uk

SONYA S. LIM, *DePaul University*
sonya.lim@depaul.edu

JINHAN PAE, *Korea University*
jinhanpae@korea.ac.kr

CHOONG-YUEL YOO, *KAIST**
cyoo@business.kaist.ac.kr

April 2017

* Corresponding author. Tel: +82-2-958-3326; Fax: +82-2-958-3604
Associate Professor of Accounting
Graduate School of Finance & Accounting
KAIST College of Business
Korea Advanced Institute of Science and Technology (KAIST)

We thank Peter Pope (the editor), an anonymous referee, Larry Brown, Logan Steele, Byungjin Kwak, Kelvin Law, Sangwoo Lee and Hyungshin Park for helpful comments and suggestions. We are also grateful to the seminar participants at 2015 AAA Midwest Region Meeting, 2014 AAA/Deloitte Foundation/J. Michael Cook Doctoral Consortium, 2013 Temple University Accounting Conference, 2013 AAA Annual Meeting, 2013 International Symposium on Forecasting, 2013 Korean Securities Association Conference, 2013 KAA International Conference, KAIST-Korea University Joint Accounting Research Workshop, Seoul National University and Yonsei University for helpful comments. Jinhan Pae acknowledges the financial support from the Korea University Research Grant. Choong-Yuel Yoo acknowledges the financial support from KAIST Internal Research Grant.

Do Analysts Who Understand Accounting Conservatism Exhibit Better Forecasting Performance?

Abstract

This study investigates the performance of analysts when they match the asymmetric timeliness of their earnings forecast revisions (i.e., asymmetric forecast timeliness) with the asymmetric timeliness of firms' reported earnings (i.e., asymmetric earnings timeliness). We find that better timeliness-matching analysts produce more accurate earnings forecasts and elicit stronger market reactions to their forecast revisions. Further, better timeliness-matching analysts issue less biased earnings forecasts, more profitable stock recommendations and have more favorable career outcomes. Overall, our results indicate that analysts' ability to incorporate conditional conservatism into their earnings forecasts is an important reflection of analyst expertise and professional success.

Keywords: Conditional Conservatism; Asymmetric Timely Loss Recognition; Equity Analyst; Forecasting Performance; Stock Recommendation; Career Outcome

1. Introduction

This study examines whether analysts exhibit better performance when they match the asymmetric timeliness of their earnings forecast revisions (hereafter, asymmetric forecast timeliness) with the asymmetric timeliness of firms' reported earnings (hereafter, asymmetric earnings timeliness). A number of studies document that firms recognize bad news in a timelier manner than good news in their earnings; this is referred to as *conditional conservatism* (e.g., Basu, 1997).[1] Furthermore, prior studies find that conditional conservatism exhibits substantial time-series and cross-sectional differences (see Watts, 2003b; for a comprehensive literature review). That is, the level of conditional conservatism changes over time (Beaver et al., 2012) and varies according to accounting practices, to economic conditions, and to institutional factors, which can differ across firms, industries and countries (Ball et al., 2000, 2003; Barth et al., 1999, 2005; and Lara et al., 2009).

Since one of the major tasks of sell-side analysts is to produce accurate earnings forecasts by utilizing all available public and private information (e.g., Mikhail et al., 1997, 1999; Hong et al., 2000; and Hong and Kubik, 2003), analysts may have an incentive to decipher and incorporate the differing levels of conditional conservatism into their earnings forecasts. Accordingly, researchers have examined whether analysts incorporate conditional conservatism into their forecasts. For example, Helbok and Walker (2004) and Sohn (2012) find that analysts are, on average, aware of the conditionally conservative nature of reported earnings and update their earnings forecasts accordingly. However, Louis et al. (2008) and Pae and Thornton (2010) find

[1] In this paper, we focus on the concept of conditional accounting conservatism. This contrasts with unconditional accounting conservatism, which lowers earnings or book value of equity independently of news. See Ball and Shivakumar (2005) and Beaver and Ryan (2005) for further discussions. We use conditional conservatism and asymmetric earnings timeliness interchangeably throughout the paper.

that analysts fail to fully incorporate the implications of conditional conservatism into their earnings forecasts, resulting in inefficient forecasts. The aforementioned studies often limit their investigations to addressing only the question of whether analysts—on average—incorporate conditional conservatism in their forecasts; they for the most part ignore differences among individual analysts.

Hugon and Muslu (2010) explore how analysts' forecasting performance is affected by the issuance of conservative forecasts. More specifically, they find that analysts elicit greater market reactions to their forecast revisions when they are more conservative than their peers, but they do not condition their results on a firm's conditional conservatism. Hugon and Muslu attribute the finding to investors' demand for more conservative analysts, owing to a pervasive optimism among sell-side analysts.

Our study extends the literature by introducing a measure that captures the extent to which an analyst revises her forecast revision asymmetrically and matches the levels of asymmetric timeliness in her forecast revisions and earnings of the firm she follows. Our measure of the timeliness match is designed to capture analysts' understanding of conservative accounting practices and to apply this property when they revise their forecasts. We thus develop the following hypotheses regarding the effects of the timeliness match on analyst performance.

First, we predict that analysts who better match their asymmetric forecast timeliness with firms' asymmetric earnings timeliness provide more accurate earnings forecasts (H1). Given the large variation in the levels of conditional conservatism across firms, we posit that analysts will differ in their ability to discern and incorporate the differing levels of conditional conservatism across firms into their forecast revisions. If an analyst is conservative but does not know the level of a target firm's conditional conservatism, then being conservative may not necessarily improve her performance. For instance, she may be overly conservative for a firm that has a low level of conditional conservatism. However, astute analysts will be capable of inferring the level of conditional conservatism of a firm by observing its past reported earnings and news reflected in stock returns. In effect, they can avoid over- or under-shooting their asymmetric forecast timeliness by correctly incorporating the level of the target firm's asymmetric earnings timeliness into their forecast revisions.

Clement et al. (2011) view analysts' understanding of public signals (e.g., stock returns) as their capability of fine-tuning the use of public signals based on the level of signal informativeness. Similarly, we argue that analysts who can understand conditional conservatism and can decipher its implication for future earnings will fine-tune their asymmetric forecast timeliness in accordance with asymmetric earnings timeliness. That is, astute analysts will match the extent to which they reflect bad versus good news into earnings forecasts (i.e., asymmetric forecast timeliness) with the extent to which the firm they follow reflects bad versus good news into its reported earnings (i.e., asymmetric earnings timeliness). To the extent that the timeliness-matching behavior reflects an analyst's well-informed response to or expertise in understanding conditional conservatism, analysts who match better will exhibit superior forecast accuracy.

Second, we predict that the market responds more strongly to forecast revisions of analysts who better match their asymmetric forecast timeliness with firms' asymmetric earnings timeliness (H2). Prior research suggests that the market values analysts who produce accurate earnings forecasts (e.g., Stickel, 1992; Park and Stice, 2000; and Brown and Mohammad, 2010). It also suggests that the market responds more strongly to analysts who understand the informativeness of public signals and who accordingly fine-tune the use of these signals (Clement et al., 2011). Further, Barth et al. (2014) find that price adjustments to the announcements of conservative earnings are delayed. They attribute the finding to the conservative nature of earnings that requires investors to spend more time in interpreting the earnings information. Therefore, if some analysts better understand cross-sectional differences in conditional conservatism and successfully match their asymmetric forecast timeliness with the target firm's asymmetric earnings timeliness, then such matching behavior could be one way of signaling their superior expertise. The market will factor in analysts' timeliness-matching performance when responding to these analysts' forecasts.

It is important to note that we are not trying to examine the effect of analysts' conservatism traits on their forecasting performance as in Hugon and Muslu (2010). Hugon and Muslu define an analyst as conservative if she responds to bad news more strongly than her peer analysts when revising her forecasts. Thus, they focus on distinguishing more conservative analysts from less conservative ones. However, in our study, given large variations in the level of conditional conservatism across firms, analysts need not necessarily be more conservative to be identified as competent timeliness-matching analysts. In fact, being more conservative could lead to poor timeliness-matching for an analyst. The following real-life example in Figure 1 illustrates two cases where an analyst, Jane, outperforms her peer analyst, John as she better matches her asymmetric forecast timeliness with the target firms' asymmetric earnings timeliness.[2]

Panel A of Figure 1 shows the first case where two analysts, Jane and John, follow an aggressive firm, Union Pacific Corp (the level of asymmetric earnings timeliness is -0.015). According to our measure of an analyst's asymmetric forecast timeliness, Jane issues aggressive forecast revisions whereas John issues conservative forecast revisions for the firm (Jane: -0.072 vs. John: 0.150). Thus, as a result of her better timeliness matching, Jane issues relatively more

[2] While Figure 1 is based on actual analysts' forecasts for Union Pacific and Landstar System, analysts' names are pseudonyms and not associated their real names and gender.

accurate forecasts for the firm as well as elicits stronger market reactions to her forecast revisions, compared to John who issues conservative forecast revisions for the aggressive firm. In Panel B, the two analysts follow another firm, Landstar System, Inc., which is conservative according to the level of asymmetric earnings timeliness (0.069). In contrast to Panel A where Jane issues aggressive forecast revisions for Union Pacific Corp., she now revises her forecasts in a more conservative way, compared to John, in order to better match her asymmetric forecast timeliness with the conservative firm's asymmetric earnings timeliness. As a result, compared to John, Jane continues to exhibit higher forecast accuracy and elicit stronger market reactions to her forecast revisions when following Landstar System, Inc. As such, our measure of timeliness-matching between forecast revisions and firms' earnings is distinct from Hugon and Muslu's (2010) analyst conservatism.

Our empirical results support the importance of matching the level of asymmetric forecast timeliness with that of asymmetric earnings timeliness. First, consistent with the first hypothesis, we find that our measure of the timeliness-matching is positively associated with forecast accuracy. We also find a negative relation between our timeliness-matching measure and forecast bias, suggesting that timeliness-matching analysts provide less optimistically biased forecasts.

Second, consistent with the second hypothesis, we find stronger market reactions to forecast revisions by better timeliness-matching analysts. The result suggests that the market or investors appreciate analysts' ability to match their asymmetric forecast timeliness with the target firm's asymmetric earnings timeliness.

Third, given that stock recommendations are another key output of sell-side analysts (Bradshaw, 2004), we also examine whether timeliness-matching analysts provide more profitable stock recommendations. Loh and Mian (2006) and Ertimur et al. (2007) show that more accurate analysts issue more profitable stock recommendations, suggesting a possible channel through which timeliness-matching ability influences the profitability of stock recommendations. We find a positive relation between an analyst's timeliness-matching performance and the profitability of her stock recommendations.

Finally, we examine the relation between analysts' timeliness-matching performance and their career outcomes. We find that, all else being equal, better timeliness-matching analysts are less likely to experience turnover and more likely to stay longer in the profession. Overall, these results suggest that analysts' timeliness-matching ability is an important reflection of their expertise and professional success.

The remainder of the paper is organized as follows. Section 2 describes the measurement of timeliness match and Section 3 outlines the sample selection procedure and shows descriptive statistics for the variables. Section 4 presents the main results. In Section 5 we provide the results for additional tests and robustness checks. Section 6 concludes the paper.

2. Measurement of Timeliness-Matching

2.1. Asymmetric Earnings Timeliness

In our study, we primarily use the following piecewise-linear regression of earnings on stock returns (Basu, 1997) to estimate a firm-year measure of asymmetric earnings timeliness.[3]

$$\frac{Actual\ EPS}{LagPrice} = \beta_0 + \beta_1 RET^{Annual} + \beta_2 D + \beta_3 RET^{Annual} \times D + \varepsilon, \tag{1a}$$

where *Actual EPS* is the I/B/E/S actual earnings per share, *LagPrice* is the stock price at the

[3] Khan and Watts (2009) develop a firm-year measure of conditional conservatism, C-SCORE, by expressing the incremental timeliness for bad news over good news (i.e., asymmetric earnings timeliness) as a linear function of the market-to-book ratio, size and leverage. However, in our study, C-SCORE is not an appropriate measure because we should estimate analysts' asymmetric forecast timeliness in the same way the firms' asymmetric earnings timeliness is estimated in order to assess how closely the levels of two different timeliness are aligned with each other.

beginning of the fiscal year, RET^{Annual} is the market-adjusted, buy-and-hold return over the fiscal year, D is a dummy variable equal to 1 when RET^{Annual} is negative and 0 otherwise, and β_3 is the asymmetric timeliness coefficient (ATC), which has been widely used as a measure of conditional conservatism (e.g., Pope and Walker, 1999; Giner and Rees, 2001; Pae, 2007; Ball et al., 2013; and Barth et al., 2014). In our study, we estimate Equation (1a) at the firm-year level using a firm's all past earnings and return information available from 1990 up to the preceding fiscal year for which the most recent earnings announcement is made. We define the firm's asymmetric timeliness coefficient of β_3 as our firm-year measure of asymmetric earnings timeliness ($Firm.ATC^L$).[4] We ensure the reliability of our measure by requiring at least eight observations, including the minimum of two positive and two negative values of returns (RET^{Annual}) in estimating Equation (1a) (Hugon and Muslu, 2010; Clement et al., 2011; and Heflin et al., 2014).[5] We use the I/B/E/S actual earnings rather than GAAP earnings because the majority of analysts forecast pro forma earnings (i.e., street earnings) that exclude special items such as restructuring charges and asset impairments from GAAP earnings and the I/B/E/S provides pro forma earnings after adjustments to facilitate its comparability with what analysts actually forecast (Bradshaw and Sloan, 2002; and Brown et al., 2014).[6]

Next, we propose another firm-year measure of asymmetric earnings timeliness.

---

[4] Some prior studies use the ratio of negative return response to positive return response, $(\beta_3+\beta_1)/\beta_1$, as a measure of accounting conservatism (e.g., Givoly and Hayn, 2000). We do not use the ratio measure because the ratio is hard to interpret when its denominator (β_1) is negative. In Table 1, we find that nearly half of β_1 estimates are negative. Furthermore, the ratio takes extreme values when β_1 is close to zero. Barth et al. (2014) also discuss a problem with using this ratio as the return coefficient (β_1) is often negative or insignificantly different from zero in the post-1990 periods.

[5] The maximum number of observations used in the estimation is 20.

[6] Heflin et al. (2014) find evidence on the asymmetric timeliness in pro forma earnings although its magnitude is smaller than that in GAAP earnings.

$$\frac{(Actual\ EPS - Lag\ of\ Actual\ EPS)}{LagPrice} = \beta_0 + \beta_1 RET^{Annual} + \beta_2 D + \beta_3 RET^{Annual} \times D + \varepsilon, \qquad (1b)$$

where *Lag of Actual EPS* is the preceding fiscal year's I/B/E/S actual EPS. β_3 from Equation (1b) is our second measure of asymmetric earnings timeliness of a firm in a year, which will be denoted by $Firm.ATC^C$. Similar to Equation (1a), we estimate Equation (1b) using a firm's all past earnings and return information available from 1990 up to the preceding fiscal year for which the most recent earnings announcement is made. We also impose the same estimation constraints as Equation (1a) by requiring at least eight observations, including two positive and two negative return observations.

Note that we use the change in actual EPS, rather than the level of actual EPS, for the dependent variable in Equation (1b). While using Equation (1b) is not the most popular approach to estimate the asymmetric timeliness in a firm's earnings, it has often been employed in previous studies (e.g., Ball et al., 2013). We utilize this change specification of Equation (1b) to introduce an alternative measure of a firm's asymmetric earnings timeliness because we use a similar change specification when estimating the asymmetric timeliness in analysts' forecast revisions, which we will discuss in more detail in the next subsection. We expect our two measures of asymmetric earnings timeliness to complement each other and help us mitigate a potential measurement error in our match measures.[7] The match measures will be discussed in Subsection 2.3.

---

[7] We thank the Editor for drawing our attention to the on-going debate on Basu's (1997) asymmetric timeliness measure (Patatoukas and Thomas, 2011, 2016; Ball et al., 2013; Cano-Rodríguez and Núñez-Nickel, 2015; and Dutta and Patatoukas, 2016). Ball et al. (2013) show that the bias is primarily cross-sectional in nature and can be addressed by controlling for firm specific effects or by using unexpected earnings and returns. The way we measure asymmetric earnings timeliness is consistent with the suggestions by Ball et al. (2013) because we estimate Equations (1a) and (1b) in time-series for each firm and also use unexpected earnings (i.e., a change in earnings, adjusted by one-year-lagged earnings) in Equation (1b) and use market-adjusted rather than raw returns (RET^{Annual}) in both Equations (1a) and (1b). In addition, our key variable of interest is a measure of timeliness-matching (*MATCH*) which is the absolute difference between a firm's asymmetric earnings timeliness (*Firm.ATC*) and an analyst's asymmetric forecast timeliness (*Analyst.ATC*). To the extent that we measure *Firm.ATC* and *Analyst.ATC* in analogous manners, any

2.2. Asymmetric Forecast Timeliness

Our measure of analysts' asymmetric forecast timeliness is motivated by the model of the relation between analyst forecast revisions and stock returns, introduced in studies that have examined the information content of analysts' earnings forecast revisions (e.g., Givoly and Lakonishok, 1979; and Lys and Sohn, 1990). These studies find a positive association between analysts' earnings forecast revisions and stock returns, and they conclude that analysts partially incorporate public information that is reflected in stock returns (Lys and Sohn, 1990). We extend the model used by those studies by adding an indicator variable for negative stock returns and its interaction term with stock returns.[8] The resulting regression model is specified as

$$REV \ \left\{= \frac{(Current\ EPS\ forecast - Preceding\ EPS\ forecast)}{LagPrice}\right\}$$

$$= \ \beta_0 + \beta_1 RET + \beta_2 D + \beta_3 RET \times D + \varepsilon, \qquad (2)$$

where *REV* is a change in an analyst's two consecutive EPS forecasts for a firm (i.e., forecast revision). *Current EPS forecast* is an analyst's EPS forecast for the current fiscal year's earnings of a firm; *Preceding EPS forecast* is the analyst's EPS forecast for the same firm and fiscal year that immediately precedes *Current EPS forecast*; *LagPrice* is the stock price at the end of the month in which the analyst's preceding EPS forecast is made; *RET* is the market-adjusted, buy-and-hold return over the revision period starting from the date of the preceding forecast and ending on the current forecast date; and *D* is a dummy variable equal to 1 when *RET* is negative and 0 otherwise.

β_3 captures the asymmetric timeliness in an analyst's forecast revisions with respect to

potential biases in those measures are likely to be cancelled out. Nevertheless, we acknowledge that the values of our asymmetric timeliness measures need to be interpreted with caution.

[8] Hugon and Muslu (2010) use a regression model similar to Equation (2) in their robustness checks (see their footnote 9).

good and bad news, which we refer to as asymmetric forecast timeliness. This corresponds to the Basu's (1997) asymmetric timeliness coefficient in Equations (1a) and (1b). β_3 is our measure of an analyst's asymmetric forecast timeliness for a firm in a year (*Analyst.ATC*). We estimate Equation (2) at the analyst-firm-year level using all past EPS forecast revisions for a firm issued by an analyst between 1990 up to the firm's most recent earnings announcement date. For each estimation of Equation (2), we require at least eight observations including the minimum of two positive and two negative return observations.

2.3. Measure of Timeliness Match

After estimating the level of an analyst's asymmetric forecast timeliness for a firm (*Analyst.ATC*) and that of the firm's asymmetric earnings timeliness ($Firm.ATC^L$ or $Firm.ATC^C$), we measure the extent to which an analyst's asymmetric forecast timeliness matches with the firm's asymmetric earnings timeliness in the following way:

$$MATCH^{L\,(C)}(i,j,t) = -1 \times |Analyst.ATC(i,j,t) - Firm.ATC^{L\,(C)}(j,t)|, \tag{3}$$

where *i*, *j* and *t* represent the analyst, firm and year, respectively. Superscripts *L* or *C* next to *MATCH* (*i*, *j*, *t*) indicate that we use $Firm.ATC^L$ or $Firm.ATC^C$ as a measure of the firm's asymmetric earnings timeliness when computing the extent of timeliness match. *MATCH* (*i*, *j*, *t*) captures an analyst's firm-year specific ability to match or align her asymmetric forecast timeliness with the firm's asymmetric earnings timeliness. In our empirical analyses, we measure *MATCH* (*i*, *j*, *t*) at firm *j*'s most recent earnings announcement date, preceding analyst *i*'s current forecast date in year *t*. This ensures that, particularly in our tests of market responses, information about an analyst's timeliness-matching performance is known to the market investors before they react to the analyst's forecast revisions.

3. Sample

3.1. Sample Selection

We obtain data from I/B/E/S, CRSP and Compustat. First, we use the I/B/E/S Detail EPS File to collect analysts' forecasts of current fiscal year earnings per share (EPS), which are referred to as one-year-ahead forecasts in I/B/E/S, and the actual EPS for U.S. firms over the period 1990 to 2010.[9] Unless stated otherwise, we use earnings forecasts that are issued after the most recent year's actual earnings announcement date and prior to the current year's earnings announcement date.[10] We obtain analysts' stock recommendations, stock returns and other fundamental data from the I/B/E/S Detail Recommendations File, CRSP and Compustat.

We impose several restrictions on the sample. First, we delete observations with a stock price less than $1, in order to avoid the effect of penny stocks and that of small denominators. Next, we only consider analysts who have made at least eight earnings forecast revisions, including a minimum of two positive and two negative revision period stock returns for a firm from 1990 up to the fiscal year preceding the current forecast date (e.g., Hugon and Muslu, 2010). Finally, after merging all data sources, we eliminate observations with missing values and mitigate the effects of outliers by winsorizing all continuous variables at the 1% and 99% levels. Our final sample for $MATCH^L$ ($MATCH^C$) contains 116,284 (106,503) analyst, firm-year, forecast-horizon observations over the period from 1998 (1999) to 2010, made by 2,287 (2,170) unique analysts covering 1,565 (1,414) unique firms.[11]

---

[9] Our sample period starts in 1990 because we need accurate forecast revision dates to measure market responses. Before the early 1990s, the forecast release date in I/B/E/S is often different from the actual forecast date (see Clement and Tse, 2003; and Hugon and Muslu, 2010). The results are qualitatively the same when we start the sample period in 1983.

[10] For example, if a firm's fiscal year ends on December 31 and the firm announces its actual earnings on February 25 every year, we use forecasts issued between two consecutive announcement dates (from February 26, 2010 until February 24, 2011) for its fiscal year 2010.

[11] Since we use earnings change as the dependent variable in Equation (1b), the $MATCH^C$ sample becomes available

3.2. Summary Statistics

Panel A of Table 1 reports the distribution of our first measure of asymmetric earnings timeliness, $Firm.ATC^L$, for 7,574 firm-year observations. Consistent with prior research on conditional conservatism (e.g., Basu, 1997), both mean and median $Firm.ATC^L$ (0.016 and 0.009) are positive, indicating that our sample firms are on average conservative. Panel B reports the distributions of our second measure of asymmetric earnings timeliness, $Firm.ATC^C$, for 6,792 firm-year observations. Overall, Panel B shows similar figures to those in Panel A.

Panel C reports the distribution of our measure of asymmetric forecast timeliness, *Analyst.ATC*, for 27,092 analyst-firm-year observations. We find that mean (median) *Analyst.ATC* is 0.005 (0.002), which is consistent with prior findings that analysts update their forecast revisions in a conservative fashion (Helbok and Walker, 2004; and Sohn, 2012). A comparison of *Analyst.ATC* with $Firm.ATC^L$ and $Firm.ATC^C$ indicates that analysts' earnings forecast revisions are on average less conservative than reported earnings, consistent with analysts downplaying bad news while highlighting good news (e.g., Francis and Philbrick, 1993; and Hayes, 1998).

Lastly, Panel D reports the distribution of our measures of the match between an analyst's asymmetric forecast timeliness and asymmetric earnings timeliness of the firm she follows. While the distributions of two match measures are highly similar to each other, $MATCH^C$ figures are relatively higher than $MATCH^L$ figures.

Table 2 presents summary statistics of the variables used in our analyses. Overall, the summary statistics are in line with those of prior research. For example, the mean of analysts' forecast revisions (*REV*) is slightly below zero (-0.001), indicating that analysts on average revise

---

a year later than the $MATCH^L$ sample.

their earnings forecasts downwards as the year progresses (e.g., Lys and Sohn, 1990). The means of analyst- and firm-specific characteristics such as firm-specific experience (*FEXP*), the number of firms the analyst follows (*NFIRM*), brokerage size (*BSIZE*), book-to-market ratio (*BM*), and firm size (*SIZE*) are also similar to those in Clement et al. (2011).[12]

Next, in Panel A of Table 3, we show whether and how our first measure of timeliness match, $MATCH^L$, is associated with analyst, forecast and firm-specific characteristics. A higher $MATCH^L$ indicates a better match between an analyst's asymmetric forecast timeliness and asymmetric earnings timeliness of the firm she follows. Since we rank analyst-firm-year observations into quintiles based on $MATCH^L$, the mean value of $MATCH^L$ monotonically increases from -0.269 in quintile 1 (worst match quintile) to -0.009 in quintile 5 (best match quintile).

Univariate comparisons of analyst, forecast, and firm characteristics between the best and worst $MATCH^L$ quintiles in Panel A indicate the following. First, a lower $MATCH^L$ score is associated with a higher value of a firm's asymmetric earnings timeliness (mean $Firm.ATC^L$: 0.054 in quintile 1 vs. 0.004 in quintile 5) and a higher value of an analyst's asymmetric forecast timeliness (mean $Analyst.ATC^L$: 0.008 in quintile 1 vs. 0.004 in quintile 5). That is, while analysts are on average more conservative in their forecasts when they cover more conservative firms, they err to a greater extent in aligning their asymmetric forecast timeliness with asymmetric earnings timeliness.

Second, Hugon and Muslu's (2010) "analyst conservatism" measure (*HM_CONSV*) is relatively constant across $MATCH^L$ quintiles (3.03 in quintile 1 vs. 3.06 in quintile 5). It appears

[12] Variable definitions are provided in Appendix.

that there is no systematic relation between analysts' timeliness match and the level of relative analyst conservatism, suggesting that our $MATCH^L$ measure captures a different aspect of analyst characteristics than what Hugon and Muslu (2010) measure does.

As regards other analyst-specific characteristics, we find that better timeliness-matching analysts have longer firm-specific experience (*FEXP*: 6.31 in quintile 1 vs. 6.94 years in quintile 5), have longer general experience (*GEXP*: 9.81 vs. 10.32 years), and cover more diverse industries (*NIND*: 3.78 vs. 3.99 industries). Forecast revisions of better timeliness-matching analysts are characterized as being issued less frequently for a firm (*FREQ*: 6.27 vs. 5.74 revisions), later in a year [*Avg* (*HORIZON*): 175.62 vs. 172.78 days] and more immediately after other analysts' forecast revisions [*Avg* (*DaysElapsed*): 10.95 vs. 9.75 days]. As for firm characteristics, we find that better timeliness-matching analysts cover firms with lower book-to-market ratios (*BM*: 0.56 vs. 0.39), larger size (*SIZE*: 14.97 vs.15.46), less volatile stock returns [*Avg* (*RetVolatility*): 0.121 vs. 0.108], and better earnings quality (*EarnQuality*: -0.030 vs. -0.029). Lastly, we find that the timeliness-matching expertise is positively related to past accuracy (*AvgAccuracy*: -0.016 vs. -0.005) and past forecast error (*AvgFE*: -0.005 vs. -0.001).

In Panel B of Table 3, we find that our second measure of timeliness match ($MATCH^C$) is negatively related to the number of firms followed by an analyst (*NFIRM*) but positively related to the size of her brokerage house (*BSIZE*), suggesting that better timeliness-matching analysts cover fewer firms in a year and work with larger brokerage houses. For the rest of the variables, Panel B provides similar results to those in Panel A.

In Panel C, we further examine the association between timeliness-matching performance and analyst, forecast and firm-specific characteristics using regression analyses. The dependent variables are $MATCH^L$ in the first two columns and $MATCH^C$ in the next two columns. Across the columns, we find that coefficients on almost half of the independent variables are statistically significant, suggesting that those characteristics play a significant role in explaining the timeliness-matching performance. For example, an analyst's timeliness-matching performance is significantly associated with the firm-specific experience (*FEXP*), the number of industries following (*NIND*), firm size (*SIZE*), and the past forecast accuracy (*AvgAccuracy*). We also find that analysts tend to match the asymmetric timeliness between forecast revisions and earnings better when they have fewer firms in their coverage portfolio (*NFIRM*) or when they cover firms with lower book-to-market ratio (*BM*).

4. Empirical Results

4.1. Timeliness-Matching Analysts and Forecast Accuracy

In this subsection, we investigate whether an analyst's timeliness-matching performance is associated with her forecast accuracy. Specifically, we estimate the following OLS regression:

$$\begin{aligned}
&ACCURACY = \\
&\quad \alpha_0 + \alpha_1\, MATCH^{L\,(C)} + \alpha_2\, Firm.ATC^{L\,(C)} + \alpha_3\, HM_CONSV \\
&\quad + \alpha_4\, FEXP + \alpha_5\, GEXP + \alpha_6\, NFIRM + \alpha_7\, NIND + \alpha_8\, BSIZE + \alpha_9\, FREQ \\
&\quad + \alpha_{10}\, HORIZON + \alpha_{11}\, DaysElapsed + \alpha_{12}\, BM + \alpha_{13}\, SIZE \\
&\quad + \alpha_{14}\, RetVolatility + \alpha_{15}\, EarnQuality + \alpha_{16}\, AvgAccuracy + \alpha_{17}\, AvgFE \\
&\quad + \Sigma\, \alpha_y\, Year\ fixed\ effects + \Sigma\, \alpha_z\, Industry\ fixed\ effects + \varepsilon, \qquad (4)
\end{aligned}$$

where *ACCURACY* is negative one times the absolute difference between an analyst's earnings forecast and the firm's actual earnings, scaled by the stock price on the last trading day of the month in which the analyst's forecast is made. $MATCH^{L\,(C)}$ is our measure of an analyst's timeliness-matching performance, calculated as negative one times the absolute difference between an analyst's asymmetric forecast timeliness (*Analyst.ATC*) and a firm's asymmetric earnings timeliness ($Firm.ATC^{L\,(C)}$). In Equation (4), we control for firm, analyst, and forecast-specific characteristics that are known to affect forecast accuracy (e.g., Clement and Tse, 2005; and Clement et al., 2011): Hugon and Muslu's (2010) analyst conservatism (*HM_CONSV*), firm-specific experience (*FEXP*), general experience (*GEXP*), number of firms following (*NFIRM*), number of industries following (*NIND*), brokerage size (*BSIZE*), forecast frequency (*FREQ*), forecast horizon (*HORIZON*), days elapsed since last forecast (*DaysElapsed*), book-to-market ratio (*BM*), firm size (*SIZE*), return volatility (*RetVolatility*), earnings quality (*EarnQuality*), past average forecast accuracy (*AvgAccuracy*), and past average forecast error (*AvgFE*). In addition, we include year and industry fixed effects in the regression model. Standard errors are clustered by firm and year to allow for intra-group correlations in residuals within each firm and analyst group (Petersen, 2009; and Gow et al., 2010). Detailed variable definitions are provided in Appendix. Our prediction for the first hypothesis (H1) is that the coefficient on $MATCH^{L\ (C)}$ will be positive (i.e., $\alpha_1 > 0$).

Table 4 shows the estimation results from OLS regressions of Equation (4). We report the results based on $MATCH^{L}$ in columns (1) to (3) and $MATCH^{C}$ in columns (4) to (6). Since we obtain inferentially similar results irrespective of the measure of timeliness match, we mainly discuss the results based on $MATCH^{L}$ in columns (1) to (3).

In column (1), we find a positive and significant coefficient (0.031, *t*-statistic = 5.90) on $MATCH^{L}$, consistent with our first hypothesis (H1).[13] In particular, we note that the result is not only statistically significant but also economically meaningful: one-standard deviation increase in

[13] It may be possible that analysts' discretion about what components of GAAP earnings to be excluded in their earnings forecasts could affect forecast accuracy. However, this alternative explanation is less likely to be a main reason for the results in Table 4, because we measure analyst forecast accuracy against pro forma earnings provided by the I/B/E/S to mitigate the effect of exclusion. Furthermore, exclusion of transitory items may not explain our other findings such as stronger market reactions, profitable stock recommendations, and better career outcomes.

the timeliness-matching performance is associated with an improvement in forecast accuracy by 11.8% of its standard deviation.[14]

In Column (2), we control for analyst, forecast, and firm-specific characteristics, including the average of past forecast accuracy (*AvgAccuracy*) and the average of past signed forecast error (*AvgFE*). A significant and positive coefficient on $MATCH^L$ (0.008, *t*-statistic = 2.11) suggests that analysts' timeliness-matching performance has incremental explanatory power beyond control variables such as past forecast accuracy and past forecast bias in explaining forecast accuracy of the current earnings forecasts. Most of the estimated coefficients on other control variables are in line with prior studies (e.g., Kumar, 2010; and Kim et al., 2011). For instance, we find a negative and significant coefficient (-0.055, *t*-statistic = -11.69) on *HORIZON*, which indicates that analysts provide more accurate forecasts as the actual earnings announcement date comes closer. We also find a positive and significant coefficient (0.001, *t*-statistic = 2.69) on *SIZE*, which indicates that analysts provide more accurate earnings forecasts when they follow larger firms, for which more information is available. Also, we use *RetVolatility* as a proxy for forecasting difficulty, and we find a negative and significant coefficient (-0.076, *t*-statistic = -4.46), suggesting that analysts provide less accurate forecasts when they follow a firm with highly volatile stock returns.

Next, we further investigate whether the relation between our match measures and forecast accuracy is driven by the effects of other conservatism-related dimensions. To address this concern, in column (3), we additionally control for analyst conservatism (*HM_CONSV*) and firms' asymmetric earnings timeliness ($Firm.ATC^L$), both of which are known to affect forecast accuracy (Louis et al., 2008; Hugon and Muslu, 2010; and Pae and Thorton, 2010). We find that our results

[14] This calculation of 11.8% = (0.110×0.031)/0.029 is based on the standard deviation of $MATCH^L$ of 0.110 (in Panel D, Table 1) and the standard deviation of *ACCURACY* of 0.029 (in Table 2).

continue to remain significant after controlling for analyst conservatism and firms' asymmetric earnings timeliness. Finally, we report similar results when $MATCH^C$ is employed in columns (4) to (6). The coefficients on $MATCH^C$ are consistently significant across all specifications.

Overall, in Table 4 we find supporting evidence for our first hypothesis (H1) that analysts provide more accurate earnings forecasts when they better match their asymmetric forecast timeliness with the asymmetric earnings timeliness of the target firm. Moreover, the evidence lends additional support to our notion that matching timeliness between an analyst's forecast revision and earnings of the firm she follows is more important than just her being conservative or covering less conservative firms.

4.2. Timeliness-Matching Analysts and Market Responses

In this subsection, we examine whether the market participants respond more strongly to the forecast revisions of analysts who better match their asymmetric forecast timeliness with asymmetric earnings timeliness of the firm they follow (H2). In examining the effect of analysts' timeliness-matching performance on market reactions to earnings forecasts, we estimate the following OLS regression:

$$\begin{aligned} CAR\,(-1, +1) = {} & \gamma_0 + \gamma_1\, REV + \gamma_2\, MATCH^{L\,(C)} + \gamma_3\, REV \times MATCH^{L\,(C)} \\ & + \Sigma\, \gamma_m\, Controls + \Sigma\, \gamma_n\, REV \times Controls \\ & + \Sigma\, \gamma_r\, Year\ fixed\ effects + \Sigma\, \gamma_s\, Industry\ fixed\ effects + \varepsilon. \end{aligned} \tag{5}$$

CAR (-1, +1) is the three-day market-adjusted, cumulative abnormal return for a firm from trading day -1 to trading day +1, where trading day 0 is an analyst's forecast revision date. *REV* is an analyst's forecast revision for the firm, measured as the difference between the analyst's two consecutive (i.e., current and immediately preceding) earnings forecasts, scaled by the closing stock price on the last trading day of the month in which the analyst's immediately preceding forecast is made. $MATCH^{L\ (C)}$ is our measure of an analyst's timeliness-matching performance. *Controls* refers to the vector of control variables that are used in Equation (4). We further include the interaction terms between forecast revision (*REV*) and control variables, year and industry fixed effects. Standard errors are clustered by firm and year (Petersen, 2009). Detailed variable definitions are provided in Appendix. For our second hypothesis (H2), we predict that the coefficient on $REV \times MATCH^{L\ (C)}$ will be positive (i.e., $\gamma_3 > 0$).

In Table 5, we report the estimation results from the OLS regression model of Equation (5). We use $MATCH^{L}$ in columns (1) to (3) and $MATCH^{C}$ in columns (4) to (6). Irrespective of the measure of an analyst's timeliness-matching performance, we find consistent results across columns in Table 5. First, in columns (1) and (4), we estimate the regression of Equation (5) without control variables. We find positive and significant coefficients on the interaction term between forecast revision and our measure of timeliness match, $REV \times MATCH^{L\ (C)}$, supporting our prediction (H2).

In columns (2) and (5), we control for analyst, forecast, and firm characteristics that are known to affect short-term market reactions to analyst forecasts (e.g., Clement et al., 2011). We find that the coefficient estimates on $REV \times MATCH^{L\ (C)}$ remain significant and positive.

In columns (3) and (6), we further control for Hugon and Muslu's (2010) analyst conservatism and firms' asymmetric earnings timeliness. Consistent with Hugon and Muslu's finding, positive and significant coefficients on $REV \times HM\_CONSV$ indicate that the market reacts more strongly to forecast revisions of analysts who issue more conservative forecasts. More importantly, the coefficients on $REV \times MATCH^{L\ (C)}$ remain positive and significant even after controlling for analyst conservatism and firms' asymmetric earnings timeliness.

In sum, the results in Table 5 are in support of our prediction (H2) that analysts who better match their asymmetric forecast timeliness with asymmetric earnings timeliness of the target firm elicit stronger market reactions to their forecast revisions.

4.3. Overall Timeliness-Matching Ability

Thus far, we have demonstrated that analysts who match the levels of asymmetric forecast timeliness and asymmetric earnings timeliness exhibit better forecasting performance. However, since our timeliness-match measure (*MATCH*) is defined at the analyst-firm-year level, it also seems possible that we may also capture some analysts who randomly achieve a higher level of timeliness match for a firm by luck, not by their ability to understand conditional conservatism.[15] Thus, in this subsection, we specifically address this concern by using an alternative measure of timeliness match, which we believe can mitigate this measurement error.

Specifically, we use the mean level of an analyst's timeliness-match for all firms she covers in a year (*Mean of MATCH*). The rationale for using the mean value is very straightforward. An analyst may occasionally achieve a superior timeliness match for a certain firm by luck. However, if the analyst does not have good understanding of the asymmetric timeliness of earnings, such superior matching performance will not be repeated because it is very unlikely to have a continuation of luck. From this perspective, we take the average of an analyst's timeliness-matching performance (*MATCH*) for all firms that she covers in a given year and use the average level (*Mean of MATCH*) as an alternative measure that captures the analyst's overall timelines-matching ability.

In Table 6, we re-estimate Equations (4) and (5) after replacing *MATCH* with *Mean of*

[15] We appreciate the editor for pointing out this possibility.

MATCH, which is defined at the analyst-year level. In Panel A, we find that our results for the first hypothesis (H1) remain strong and significant across all columns, suggesting that better timeliness-matching analysts do have higher forecast accuracy. We also find that, in Panel B, our results for the second hypothesis (H2) that better timeliness-matching analysts elicit stronger market reactions to their forecast revisions hold qualitatively the same as those in Table 5. Taken all together, the results in Table 6 alleviate the concern that our findings are mainly attributable to analysts who randomly achieve a superior timeliness-match for a firm.

5. Additional Tests

5.1. Timeliness-Matching Analysts and Forecast Bias

We investigate another aspect of analysts' forecast properties, optimistic bias, in this subsection. A number of prior studies document analysts' systematic tendency to issue optimistically biased forecasts (Hong and Kubik, 2003; Ke and Yu, 2006; and Barron et al., 2013). Thus, we examine the relationship between the timeliness-matching measure and bias in analyst forecasts. In Table 7, we present results for analyst forecast bias tests using the OLS regressions of Equation (4) after replacing the dependent variable with *Forecast Optimism*. *Forecast Optimism* is measured as the difference between an analyst's earnings forecast for a firm and the firm's actual earnings, scaled by the stock price on the last trading day of the month in which the analyst's forecast is made.

A higher value of *Forecast Optimism* corresponds to a more optimistically biased forecast. In column (1), we find a negative and significant coefficient on $MATCH^{L}$ (-0.017, *t*-statistic = -4.42), suggesting that better timeliness-matching analysts provide less optimistically biased forecasts. In other columns, we find inferentially same results irrespective of the measure of timeliness match or set of control variables we use. Overall, the results in Table 7 with those in Table 4 indicate that analysts with better timeliness-matching expertise provide less biased and more accurate earnings forecasts.

5.2. Timeliness-Matching Analysts and Stock Recommendation

Analysts' stock recommendations that reflect their opinions about a firm's intrinsic value relative to current stock price (e.g., Stickel, 1985) are one of the key outputs of sell-side analysts. In this subsection, we examine whether analysts with better timeliness-matching performances provide more profitable recommendations than those analysts who poorly match their asymmetric forecast timeliness with asymmetric earnings timeliness.

Since analyst recommendations retain investment values at least up to six months and their recommendations are rarely revised or reiterated in a year (Womack, 1996; and Bradshaw, 2004), we focus on recommendation profitability over three, six months and one year in the empirical analyses. Specifically, we measure *3-Month Profitability, 6-Month Profitability,* and *1-Year Profitability* as the market-adjusted buy-and-hold return for a firm over the period starting from the day before the recommendation date and ending on the earlier of three, six, or twelve months or two days before the recommendation is revised or reiterated, respectively. Following Mikhail et al. (1999), we assume that we take a $1 long position in strong buy and buy recommendations (I/B/E/S codes=1 and 2) and a $1 short position in strong sell and sell recommendations (I/B/E/S codes=4 and 5).[16]

Table 8 reports the results from the OLS regressions of stock recommendation profitability

[16] Hold recommendation may reflect either an analyst's true neutral opinion or unfavorable opinion about the stock, owing to the analyst's incentive to avoid sell recommendations. Thus, we only use buy and sell recommendations to reflect analysts' unambiguous opinions about stocks in this analysis.

on the measure of timeliness-matching performance, analyst and firm-specific characteristics, and year and industry fixed effect dummies. Across the three different holding periods, we find consistent results: our measures of timeliness match (*MATCH*^{L} and *MATCH*^{C}) are significantly and positively associated with the profitability of stock recommendations, suggesting that analysts make more profitable stock recommendations when they match the asymmetric timeliness between forecast revisions and earnings better.

5.3. Timeliness-Matching Analysts and Career Outcomes

We have thus far examined the relation between analysts' timeliness-matching ability and various aspects of their forecasting performance. In this subsection, we explore whether analysts with better timeliness-matching ability have more favorable career outcomes. We examine three different types of analysts' career outcomes: *Turnover*, *Stay in Profession* and *Promotion*.

Turnover is equal to one if an analyst moves from one brokerage house to another on I/B/E/S, leaves the profession, or moves to another brokerage house not included on I/B/E/S in the following year and zero otherwise (Mikhail et al., 1999). *Stay in Profession* is equal to one if an analyst remains on the I/B/E/S in the following year and zero otherwise (Clement and Law, 2014). *Promotion* is equal to one if an analyst moves from a low-status to a high-status brokerage house in the following year and zero otherwise. We define a brokerage house with more than 25 analysts as a high-status brokerage house (e.g., Hilary and Hsu, 2013; and Clement and Law, 2014). As an analyst's career outcomes are determined on an annual basis and are affected by her performance regarding all firms she covers, we construct the average level of an analyst's timeliness-matching ability for all firms she covers in a year (*Mean of MATCH*$^{L\ (C)}$).

Table 9 provides results for the tests on analysts' career outcomes. In columns (1) and (2), we report the results from the probit regression in which the dependent variable is *Turnover* and the variable of interest is *Mean of* $MATCH^{L\ (C)}$. We find a significant and negative coefficient on *Mean of* $MATCH^{L\ (C)}$, suggesting that better timeliness-matching analysts are less likely to experience turnover in the following year. In columns (3) and (4), we estimate the probit regression of *Stay in Profession* and find a significantly positive coefficient on *Mean of* $MATCH^{L\ (C)}$, suggesting that better timeliness-matching analysts are more likely to stay in the profession in the following year.[17] In columns (5) and (6), we perform our analysis using the subsample of analyst-years that experience turnover. We do not find statistically significant relations between the analysts' timeliness-matching expertise (*Mean of* $MATCH^{L\ (C)}$) and *Promotion*, suggesting that better timeliness-matching analysts are not more likely to get promoted to a high-status brokerage house when they experience turnover. The insignificant results may be partly attributable to a small sample size which in general lowers the power of the test.

5.4. Analysts' Expertise in Matching Gain and Loss Timeliness

In this subsection, we measure analysts' match in terms of gain timeliness and loss timeliness separately and combined. Unlike our primary measure of analysts' timeliness match, which focuses on the incremental timeliness in recognizing bad news over good news, we now disaggregate the measure of conditional conservatism into two components, which are gain and loss timeliness.[18] We first measure an analyst's match of gain timeliness ($GAIN\_MATCH^{L(or\ C)}$) as negative one times the absolute difference in gain timeliness (β_1) between the analyst's forecast revisions and earnings of the firm she follows using Equation (2) and Equations (1a) or (1b),

[17] Our results on *Stay in Profession* need to be interpreted with caution because some analysts who disappear from I/B/E/S are promoted to research executives following brokerage mergers (Wu and Zhang, 2009).
[18] We are very grateful to an anonymous referee for this suggestion.

respectively.[19] Then we measure the analyst's match of loss timeliness ($LOSS\_MATCH^{L(or\ C)}$) as negative one times the absolute difference in loss timeliness ($\beta_1 + \beta_3$) between the analyst's forecast revisions and the firm's earnings using Equation (2) and Equations (1a) or (1b). Next, we also measure the analyst's overall performance in matching gain and loss timeliness ($AVG\_GL\_MATCH^{L(or\ C)}$) as the average of the two abilities in matching gain and loss timeliness ($GAIN\_MATCH^{L(or\ C)} + LOSS\_MATCH^{L(or\ C)}$).

In Table 10, we present results for our main hypotheses (H1: Accuracy Test and H2: Market Reaction Test) using the three measures of analysts' matching performance in gain and loss timeliness. Consistent with our main findings for the analyst expertise in timeliness-matching, we find that analysts' performance in matching gain and loss timeliness separately or combined is also informative in explaining their forecast accuracy and market reactions to forecast revisions.[20]

5.5. Analyst Conservatism versus Timeliness Match

Thus far, by controlling for Hugon and Muslu's (2010) analyst conservatism measure (*HM_CONSV*) throughout the regression analyses, we have shown that matching asymmetric timeliness between forecast revisions and earnings (*MATCH*) plays a distinct role from simply being conservative. In this subsection, we delve into this question further using subsample analyses. Specifically, we divide the sample into two subsamples according to the sample median level of analyst asymmetric forecast timeliness (*Analyst.ATC*) and examine the effect of *MATCH* in each subsample.

In untabulated tests, for each subsample of analyst conservatism, we re-estimate all

---

[19] $GAIN\_MATCH^{L\,(C)}(i,j,t) = -1 \times |\beta 1(i,j,t)\ from\ Equation\ (2)\ - \beta 1(j,t)\ from\ Equation\ (1a)\ or\ (1b)|$

[20] In untabulated tests, we find similar results for forecast bias, stock recommendation profitability and career outcomes using the analyst expertise in matching gain and loss timeliness. We do not tabulate the results for brevity.

regression models from Table 4 for accuracy tests to Table 9 for career outcome tests. Overall, we find that, even among conservative analysts, timeliness-matching still plays an important role in achieving superior forecasting performance.[21] As a robustness check, we find that results in this subsection are not qualitatively different when we make subsamples using Hugon and Musulu's (2010) measure of analyst conservatism (*HM_CONSV*) or when we use the industry-year median of analyst asymmetric forecast timeliness (*Analyst.ATC*). The results in this subsection provide further supports to our notion that matching the asymmetric timeliness captures a new aspect of analyst expertise that is distinct from an analyst being simply conservative.

5.6. Robustness Checks

We check robustness of our findings as follows. First, we attempt to enhance the comparability between the measure of asymmetric forecast timeliness (*Analyst.ATC*) and that of asymmetric earnings timeliness (*Firm.ATC*). More specifically, we estimate analyst asymmetric forecast timeliness using a return variable (*RET*) that is more comparable to the return variable (RET^{Annual}) that is used when estimating the asymmetric earnings timeliness. Note that in preceding sections, we have measured the return variable (*RET*) in Equation (2) to estimate the asymmetric forecast timeliness over the forecast revision period (an average of 61 days) that is significantly shorter than the length of a fiscal year, over which the measure of RET^{Annual} for Equations (1a) and (1b) is defined to estimate the asymmetric earnings timeliness. As a robustness check, we define an analyst's unique forecast revision for each firm-year as the difference between the last two-year-ahead earnings forecast issued before the preceding year's earnings announcement date and

[21] For career outcome tests in Table 9, we find that results become insignificant when we use the subsample of low analyst conservatism. The insignificant results could be attributable to weak statistical power owing to the smaller subsample size.

the last one-year-ahead earnings forecast for the current fiscal year.[22] As a result, the average length of analysts' unique forecast revision periods extends considerably from 61 days to 372 days. In un-tabulated tests, we re-estimate Equation (2) using those extended forecast revisions and find that our main findings remain inferentially the same, ensuring that the difference in the length of return windows does not affect our findings.

Second, we repeat all analyses using total assets per share or book value of equity per share, instead of stock price, as alternative deflators for the actual EPS, change in the actual EPS, analyst forecast revision, and forecast accuracy in Equations (1a), (1b), (2), and (4), respectively. In un-tabulated tests, we find that, in general, our results for forecast accuracy, market reaction, and forecast bias tests remain significant using theses alternative deflators whereas results for stock recommendation profitability and career outcome tests become weak or insignificant.

Third, we vary the minimum number of required observations from 8 to 6, 10, 12, or 15 and the minimum number of required negative (or positive) return observations to 1, 4, or 5 in the estimation of Equations (1a), (1b) and (2). In un-tabulated tests, we find that our results hold qualitatively the same when we impose different constraints.[23]

Lastly, to further ensure that our findings are not sensitive to the choice of analyst conservatism control, we re-estimate all regression models for accuracy tests (Table 4) to career

---

[22] For example, suppose a firm with a December 31 fiscal year end. The firm announces its actual earnings on March 31 every year. If an analyst issued her two-year ahead forecasts for the firm's earnings of fiscal year 2010 in June 2009, October 2009, and in February 2010 and one-year-ahead forecasts in June 2010, in October 2010, and in February 2011, we calculate her revision using the last two-year-ahead forecast in February 2010 and the last one-year-ahead forecast in February 2011 in order to force the revision window close to one year.

[23] Our main findings for accuracy test (H1) and market reaction test (H2) remain qualitatively the same, but results for forecast bias, stock recommendation profitability, and career outcome are rather weak. In untabulated tests, we only vary constraints imposed on Equation (2) while holding the constraints for Equations (1a) and (1b) constant. We find that results remain robust even when at least 30 total, 10 positive, and 10 negative return observations are required in estimating Equation (2).

outcome tests (Table 9) after controlling for Hugon and Muslu's (2010) measure of analyst conservatism (*HM_CONSV*) in addition to our measure of an analyst's asymmetric forecast timeliness (*Analyst.ATC*). In untabulated tests, we find that results remain qualitatively the same.

6. Conclusion

This study investigates whether the extent to which an analyst matches the levels of asymmetric timeliness in her forecast revisions and earnings of the firm she follows affects her forecasting performance. We find that analysts produce more accurate earnings forecasts and elicit stronger market reactions to their forecasts when they better match or align their asymmetric forecast timeliness with firms' asymmetric earnings timeliness. We also find evidence that such timeliness-matching analysts issue less biased earnings forecasts, more profitable stock recommendations, and have more favorable career outcomes. We document that the effect of the analyst's timeliness-match on their performance and career outcomes is distinct from those of pre-existing determinants or other analyst attributes related to conservatism. Overall, our results imply that analysts' ability to understand firms' conditional conservatism and thereby adjust their asymmetric timeliness in forecast revisions in accordance with that of earnings serves as an important source of analyst expertise.

Our findings on the benefits of analyst timeliness-matching expertise may offer practical implications for market participants. Flexibility of accounting standards, coupled with managers' diverse reporting incentives, engenders a wide variation in the levels of asymmetric earnings timeliness over time, and across firms and countries (Watts, 2003b). Analysts and investors can benefit from analyzing factors that influence the level of asymmetric earnings timeliness, such as contracting, litigation, and political costs (Watts, 2003a). Brokerage houses can also benefit from our study. They often hire scientists or engineers as analysts; however, the accounting knowledge of those analysts is incommensurate with their superb technological and industrial expertise. For instance, half of Morgan Stanley healthcare analysts do not have formal accounting education at the undergraduate or graduate level (Morgan Stanley, 2012). To further improve such specialist analysts' forecasting performance, brokerage houses may consider fostering their analysts' development of accounting expertise by, for example, offering some forms of in-house training.

Our study also offers a methodological contribution to the analyst literature by proposing a direct measure of analysts' understanding of accounting information. Prior studies have used indirect measures such as analysts' experience as a proxy for their understanding of accounting information (e.g., Bradshaw et al., 2001; and Drake and Myers, 2011). In contrast, we directly measure the extent to which analysts understand accounting practices and choices by comparing the levels of analysts' asymmetric forecast timeliness and firms' asymmetric earnings timeliness.

Finally, we conclude by offering avenues for future research. It would be interesting to focus on analysts' matching expertise in other areas than conditional conservatism. Also, given the heterogeneous level of conditional conservatism across countries (Giner and Rees, 2001), future research may examine whether there exists a shift in the determinants or consequences of analysts' timeliness-matching expertise across countries with different regulatory regimes and legal traditions (e.g., civil, code, and common law). Lastly, in light of the on-going debate on the bias in Basu's (1997) asymmetric timeliness measure, it would also be worth to develop alternative measures of conditional conservatism that can be applied to both of firms' earnings and analysts' forecasts and examine the effect of match between the two.

References

Ball, R., S.P. Kothari and V.V. Nikolaev (2013), 'On Estimating Conditional Conservatism', *The Accounting Review*, Vol. 88, No. 3, pp. 755-87.

Ball, R., S.P. Kothari and A. Robin (2000), 'The Effect of International Institutional Factors on Properties of Accounting Earnings', *Journal of Accounting Economics*, Vol. 29, No. 1, pp. 1-51.

Ball, R., A. Robin and J.S. Wu (2003), 'Incentives versus Standards: Properties of Accounting Income in Four East Asian Countries', *Journal of Accounting and Economics,* Vol. 36, Nos. 1-3 (December), pp. 235-70.

Ball, R. and L. Shivakumar (2005), 'Earnings Quality in UK Private Firms: Comparative Loss Recognition Timeliness', *Journal of Accounting and Economics*, Vol. 39, No. 1, pp. 83-128.

Barron, O.E., D. Byard and L. Liang (2013), 'Analyst Pessimism and Forecast Timing', *Journal of Business Finance and Accounting*, Vol. 40, Nos. 5-6, pp. 719-39.

Barth, M.E., W.H. Beaver, J.R.M. Hand and W.R. Landsman (1999), 'Accruals, Cash Flows, and Equity Values', *Review of Accounting Studies*, Vol. 4, No. 3, pp. 205-29.

Barth, M.E., W.H. Beaver, J.R.M. Hand and W.R. Landsman (2005), 'Accruals, Accounting-Based Valuation Models and the Prediction of Equity Values', *Journal of Accounting, Auditing, and Finance,* Vol. 20, No. 4, pp. 311-45.

Barth, M.E., W.R. Landsman, V. Raval and S. Wang (2014), 'Conservatism and the Information Content of Earnings', Working paper (Stanford University and University of North Carolina at Chapel Hill).

Basu, S. (1997), 'The Conservatism Principle and the Asymmetric Timeliness of Earnings', *Journal of Accounting and Economics*, Vol. 24, No. 1, pp. 3-37.

Beaver, W.H., W.R. Landsman and E.L. Owens (2012), 'Asymmetry in Earnings Timeliness and Persistence: A Simultaneous Equations Approach', *Review of Accounting Studies*, Vol. 17, No. 4, pp. 781-806.

Beaver, W.H. and S.G. Ryan (2005), 'Conditional and Unconditional Conservatism: Concepts and Modeling', *Review of Accounting Studies*, Vol. 10, No. 2, pp. 269-309.

Bradshaw, M.T. (2004), 'How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations?' *The Accounting Review*, Vol. 79, No. 1, pp. 25-50.

Bradshaw, M.T., S.A. Richardson and R.G. Sloan (2001), 'Do Analysts and Auditors Use Information in Accruals?' *Journal of Accounting Research*, Vol. 39, No. 1, pp. 45-74.

Bradshaw, M.T. and R.G. Sloan (2002), 'GAAP versus The Street: An Empirical Assessment of Two Alternative Definitions of Earnings', *Journal of Accounting Research*, Vol. 40, No. 1, pp. 41-66.

Brown, L.D., A.C. Call, M.B. Clement and N.Y. Sharp (2014), 'Inside the 'Black Box' of Sell-Side Financial Analysts', *Journal of Accounting Research*, Vol. 53, No. 1, pp. 1-47.

Brown, L.D. and E. Mohammad (2010), 'Is Analyst Earnings Forecast Ability Only Firm Specific?' *Contemporary Accounting Research*, Vol. 27, No. 3, pp. 727-50.

Cano-Rodríguez, M. and M. Núñez-Nickel (2015), 'Aggregation Bias in Estimates of Conditional Conservatism: Theory and Evidence', *Journal of Business Finance and Accounting*, Vol. 42, Nos. 1-2, pp. 51-78.

Clement, M.B., J. Hales and Y. Xue (2011), 'Understanding Analysts' Use of Stock Returns and Other Analysts' Revisions When Forecasting Earnings', *Journal of Accounting and Economics*, Vol. 51, No. 3, pp. 279-99.

Clement, M.B. and K. Law (2014), 'Recession Analysts and Conservative Forecasting', Working paper (University of Texas at Austin and Tilburg University)

Clement, M.B. and S.Y. Tse (2003), 'Do Investors Respond to Analysts' Forecast Revisions As If Forecast Accuracy Is All That Matters?' *The Accounting Review*, Vol. 78, No. 1, pp.227-49.

Clement, M.B. and S.Y. Tse (2005), 'Financial Analyst Characteristics and Herding Behavior in Forecasting', *Journal of Finance*, Vol. 60, No. 1, pp. 307-41.

Drake, M.S. and L.A. Myers (2011) 'Analysts' Accrual-Related Over-Optimism: Do Analyst Characteristics Play a Role?' *Review of Accounting Studies*, Vol. 16, No. 1, pp. 59-88.

Dutta, S. and P.N. Patatoukas (2016), 'Identifying Conditional Conservatism in Accounting Data: Theory and Evidence', Working Paper (University of California, Berkeley)

Ertimur, Y., J. Sunder and S.V. Sunder (2007), 'Measure for Measure: The Relation between Forecast Accuracy and Recommendation Profitability of Analysts', *Journal of Accounting Research*, Vol. 45, No. 3, pp. 567-606.

Francis, J., R. Lafond, P. Olsson and K. Schipper (2007), 'Information Uncertainty and Post-Earnings-Announcement-Drift', *Journal of Business Finance and Accounting*, Vol. 34, Nos. 3-4, pp. 403-33.

Francis, J. and D. Philbrick (1993), 'Analysts' Decisions as Products of a Multi-Task Environment', *Journal of Accounting Research*, Vol. 31, No. 2, pp. 216-30.

Giner, B. and W. Rees (2001), 'On the Asymmetric Recognition of Good and Bad News in France, Germany and the United Kingdom', *Journal of Business Finance and Accounting*, Vol. 28, Nos. 9-10, pp. 1285-331.

Givoly, D. and C. Hayn (2000), 'The Changing Time-Series Properties of Earnings, Cash Flows and Accruals: Has Financial Reporting Become More Conservative?' *Journal of Accounting and Economics*, Vol. 29, No. 3, pp. 287-320.

Givoly, D. and J. Lakonishok (1979), ‘The Information Content of Financial Analysts’ Forecasts of Earnings’, *Journal of Accounting and Economics*, Vol. 1, No. 3, pp. 165-85.

Gow, I.D., G. Ormazabal, and D.J. Taylor (2010), ‘Correcting for Cross-Sectional and Time-Series Dependence in Accounting Research’, *The Accounting Review*, Vol. 85, No. 2, pp. 483-512.

Hayes, R. (1998), ‘The Impact of Trading Commission Incentives on Analysts’ Stock Coverage Decisions and Earnings Forecasts’, *Journal of Accounting Research*, Vol. 36, No. 2, pp. 299-320.

Heflin, F., C. Hsu and Q. Jin (2014), ‘Accounting Conservatism and Street Earnings’, *Review of Accounting Studies*, Vol. 20, No. 2, pp. 674-709.

Helbok, G. and M. Walker (2004), ‘On the Nature and Rationality of Analysts’ Forecasts under Earnings Conservatism’, *The British Accounting Review*, Vol. 36, No. 1, pp. 45-77.

Hilary, G. and C. Hsu (2013), ‘Analyst Forecast Consistency’, *Journal of Finance*, Vol. 68, No. 1, pp. 271-97.

Hong, H. and J.D. Kubik (2003), ‘Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts’, *Journal of Finance*, Vol. 58, No. 1, pp. 313-51.

Hong, H., J.D. Kubik and A. Solomon (2000), ‘Security Analysts’ Career Concerns and Herding of Earnings Forecasts’, *The RAND Journal of Economics*, Vol. 31, No. 1, pp. 121-44.

Hugon, A. and V. Muslu (2010), ‘Market Demand for Conservative Analysts’, *Journal of Accounting and Economics*, Vol. 50, No. 1, pp. 42-57.

Ke, B. and Y. Yu (2006), ‘The Effect of Issuing Biased Earnings Forecasts on Analysts’ Access to Management and Survival’, *Journal of Accounting Research*, Vol. 44, No. 5, pp. 965-99.

Khan, M. and R.L. Watts (2009), ‘Estimation and Empirical Properties of a Firm-Year Measure of Accounting Conservatism’, *Journal of Accounting Economics*, Vol. 48, Nos. 2-3, pp. 132-50.

Kim, Y., G.J. Lobo and M. Song (2011), ‘Analyst Characteristics, Timing of Forecast Revisions, and Analyst Forecasting Ability’, *Journal of Banking and Finance*, Vol. 35, No. 8, pp. 2158-68.

Kumar, A. (2010), ‘Self-Selection and the Forecasting Abilities of Female Equity Analysts’, *Journal of Accounting Research*, Vol. 48, No. 2, pp. 393-435.

Lara, J.M.G., B.G. Osma and F. Penalva (2009), ‘The Economic Determinants of Conditional Conservatism’, *Journal of Business Finance and Accounting*, Vol. 36, Nos. 3-4, pp. 336-72.

Loh, R.K. and G.M. Mian (2006), ‘Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?’ *Journal of Financial Economics*, Vol. 80, No. 2, pp. 455-83.

Louis, H., T. Lys and A.X. Sun (2008), 'Conservatism and Analyst Earnings Forecast Bias', Working paper (Pennsylvania State University)

Lys, T., S. Sohn (1990), 'The Association between Revisions of Financial Analysts' Earnings Forecasts and Security-Price Changes', *Journal of Accounting and Economics*, Vol. 13, No. 4, pp. 341-63.

Mikhail, M.B., B.R. Walther and R.H. Willis (1997), 'Do Security Analysts Improve Their Performance with Experience?' *Journal of Accounting Research*, Vol. 35, (Supplement), pp. 131-57.

Mikhail, M.B., B.R. Walther and R.H. Willis (1999), 'Does Forecast Accuracy Matter to Security Analysts?' *The Accounting Review*, Vol. 74, No. 2, pp. 185-200.

Morgan Stanley (2012), 'North America Research Team', Accessed December 31, 2012, http://www.morganstanley.com/institutional/research/pdf/MS_NAR.pdf.

Pae, J. (2007), 'Unexpected Accruals and Conditional Accounting Conservatism', *Journal of Business Finance and Accounting*, Vol. 34, Nos. 5-6, pp. 681-704.

Pae, J. and D.B. Thornton (2010), 'Association between Accounting Conservatism and Analysts' Forecast Inefficiency', *Asia-Pacific Journal of Financial Studies*, Vol. 39, No. 2, pp. 171-97.

Park, C.W. and E.K. Stice (2000), 'Analyst Forecast Ability and the Stock Price Reaction to Forecast Revisions', *Review of Accounting Studies*, Vol. 5, No. 3, pp. 259–72.

Patatoukas, P.N. and J.K. Thomas (2011), 'More Evidence of Bias in the Differential Timeliness Measure of Conditional Conservatism', *The Accounting Review*, Vol. 86, No. 5, pp. 1765-93.

Patatoukas, P.N. and J.K. Thomas (2016), 'Placebo Tests of Conditional Conservatism', *The Accounting Review*, Vol. 91, No. 2, pp. 625-48.

Petersen, M.A. (2009), 'Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches', *Review of Financial Studies*, Vol. 22, No. 1, pp. 435-80.

Pope, P.F. and M. Walker (1999), 'International Differences in the Timeliness, Conservatism, and Classification of Earnings', *Journal of Accounting Research*, Vol. 37, (Supplement), pp. 53-87.

Sohn, B. (2012), 'Analyst Forecast, Accounting Conservatism and the Related Valuation Implications', *Accounting and Finance*, Vol. 52, (Supplement), pp. 311-41.

Stickel, S.E. (1985), 'The Effect of Value Line Investment Survey Rank Changes on Common Stock Prices', *Journal of Financial Economics*, Vol. 14, No. 1, pp. 121-43.

Stickel, S.E. (1992), 'Reputation and Performance among Security Analysts', *Journal of Finance*, Vol. 47, No. 5, pp. 1811-36.

Watts, R.L. (2003a), ‘Conservatism in Accounting, Part I: Explanations and Implications’, *Accounting Horizons*, Vol. 17, No. 3, pp. 207-21.

Watts, R.L. (2003b), ‘Conservatism in Accounting, Part II: Evidence and Research Opportunities’, *Accounting Horizons*, Vol. 17, No. 4, pp. 287-301.

Womack, K.L. (1996), ‘Do Brokerage Analysts’ Recommendations Have Investment Value?’ *Journal of Finance*, Vol. 51, No. 1, pp. 137-67.

Wu, J.S. and A.Y. Zhang (2009), ‘What Determine Financial Analysts’ Career Outcomes during Mergers?’ *Journal of Accounting and Economics*, Vol. 47, Nos. 1-2, pp. 59-86.

Appendix

Variable Definitions

Variable	Description
ACCURACY	The measure of an analyst's forecast accuracy. *ACCURACY* is computed as -1×|*Actual EPS* –*Forecasted EPS*|, deflated by the stock price on the last trading day of the month in which an analyst's earnings forecast is made. *ACCURACY* is calculated for an analyst's forecasts of current fiscal year earnings.
Analyst.ATC	The measure of an analyst's asymmetric forecast timeliness for a firm, measured at the firm's most recent annual earnings announcement date. *Analyst.ATC* is measured by the coefficient (β_3) on $RET \times D$ of Equation (2): (*Current EPS forecast* – *Preceding EPS forecast*)/*LagPrice* = $\beta_0 + \beta_1 RET + \beta_2 D + \beta_3 RET \times D + \varepsilon$, where *Current EPS forecast* is an analyst's one-year-ahead EPS forecast for a firm and *Preceding EPS forecast* is the analyst's one-year-ahead EPS forecast for the same firm and fiscal year that immediately precedes *Current EPS forecast*. *LagPrice* is the stock price on the last trading day of the month in which the analyst's preceding EPS forecast is made. *RET* is the market-adjusted, buy-and-hold return over the revision period between the date of *Preceding EPS forecast* and that of *Current EPS forecast*. *D* is a dummy variable equal to 1 when *RET* is negative and 0 otherwise. *Analyst.ATC* (β_3) is estimated using the analyst's all past one-year-ahead EPS forecasts issued for the firm from 1990 up to the firm's most recent earnings announcement date. We require at least eight observations including the minimum of two positive and two negative return (*RET*) observations to estimate Equation (2). *Analyst.ATC* is defined at the analyst-firm-year level. *Analyst.ATC* is available from 1991 to 2010.
AvgAccuracy	The average forecast accuracy (*ACCURACY*) of an analyst's all past one-year-ahead earnings forecasts for a firm issued from 1990 up to the preceding fiscal year.
AvgFE	The average signed forecast error of an analyst's all past one-year-ahead earnings forecasts for a firm issued from 1990 up to the preceding fiscal year. Forecast error (*FE*) is measured by the difference between *Actual EPS* and *Forecasted EPS*, scaled by the last closing stock price on the month of the forecast date.
BM	Book-to-market ratio of a firm at the end of the preceding fiscal year.
BSIZE	The size of the brokerage house that employs the target analyst, measured by the total number of analysts employed by the brokerage house during the preceding fiscal year of the current forecast that the target analyst issues.
CAR (-1, +1)	The three-day market-adjusted, cumulative abnormal returns for a firm from trading day -1 to +1, where trading day 0 is an analyst's earnings forecast date.
D	A dummy variable that is equal to 1 if *RET* (or RET^{Annual}) is negative, and 0 otherwise.
DaysElapsed	Number of days elapsed since the most recent forecast by other analyst issued for the same firm-fiscal year.
EarnQuality	A firm's earnings quality, measured as negative one times the standard deviation of a firm's residuals ($\varepsilon_{j,t}$) over the past five years, where a firm-year-specific residual is obtained from the following cross-sectional regression (Francis et al., 2007): $TCA_{i,t} = CFO_{i,t-1} + CFO_{i,t} + CFO_{i,t+1} + \triangle REV_{i,t} + PPE_{i,t} + \varepsilon_{i,t}$. $TCA_{i,t}$ is firm *i*'s total current accruals in year *t*, $CFO_{i,t}$ is firm *i*'s cash flow from operation in year *t*, $\triangle REV_{i,t}$ is firm *i*'s change in revenues, and $PPE_{i,t}$ is firm *i*'s gross value of property, plant, and equipment. All variables are scaled by average total assets. The regression is estimated for each of the Fama and French 48 industry groups with at least 20 firms in a given year. We use the lagged value of a firm's earnings quality, assuming that earnings quality for firm *i* in year *t* becomes available to the market in the fourth month following the end of fiscal year *t*+1.
FEXP	An analyst's firm-specific experience, measured as the number of years the analyst has issued at least one one-year-ahead earnings forecast for the firm up to the preceding fiscal year.

Appendix continued

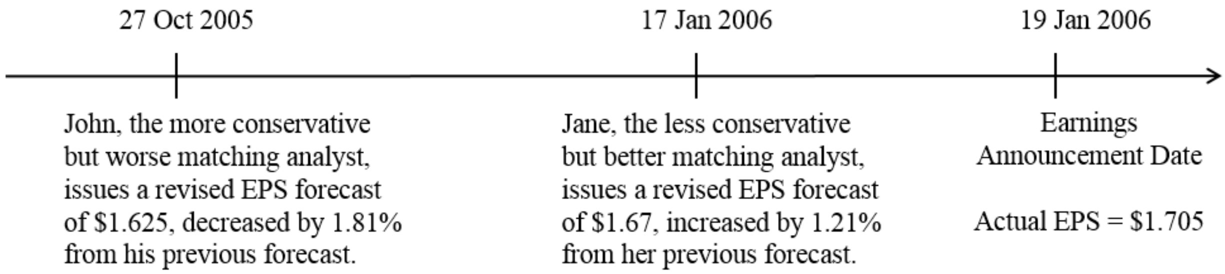
Variable	Description
Firm.ATC^{L}	The measure of a firm's asymmetric earnings timeliness, measured as the coefficient (β_3) on $RET^{Annual} \times D$ of Equation (1a): $Actual\ EPS/LagPrice = \beta_0 + \beta_1 RET^{Annual} + \beta_2 D + \beta_3 RET^{Annual} \times D + \varepsilon$. *Actual EPS* is the I/B/E/S actual EPS. *LagPrice* is the stock price at the beginning of the firm's fiscal year. RET^{Annual} is the market-adjusted, buy-and-hold return over the fiscal year. *D* is a dummy variable equal to 1 when RET^{Annual} is negative and 0 otherwise. *Firm.ATC*^{L} (β_3) is estimated at the firm-year level using a firm's all past earnings and return data from 1990 up to the preceding fiscal year for which the most recent earnings announcement is made. We require at least eight observations including two positive and two negative return (RET^{Annual}) observations to estimate Equation (1a). *Firm.ATC*^{L} is available from 1998 to 2010.
Firm.ATC^{C}	The measure of a firm's asymmetric earnings timeliness, measured as the coefficient (β_3) on $RET^{Annual} \times D$ of Equation (1b): $(Actual\ EPS - Lag\ of\ Actual\ EPS)/LagPrice = \beta_0 + \beta_1 RET^{Annual} + \beta_2 D + \beta_3 RET^{Annual} \times D + \varepsilon$. *Firm.ATC*^{C}. *Actual EPS* is the I/B/E/S actual EPS. *Lag of Actual EPS* is the firm's *Actual EPS* lagged by one year. *LagPrice* is the stock price at the beginning of the firm's fiscal year. RET^{Annual} is the market-adjusted, buy-and-hold return over the fiscal year. *D* is a dummy variable equal to 1 when RET^{Annual} is negative and 0 otherwise. *Firm.ATC*^{C} (β_3) is estimated using a firm's all past earnings and return data available from 1990 to the preceding fiscal year for which the most recent earnings announcement is made. *Firm.ATC*^{C} is defined at the firm-year level and is available from 1999 to 2010. We require at least eight observations, including two positive and two negative return (RET^{Annual}) observations.
Forecast Optimism	The measure of an analyst's forecast optimism, computed as (*Forecasted EPS- Actual EPS*) deflated by the stock price on the last trading day of the month in which an analyst's earnings forecast is made. *Forecast Optimism* is calculated for an analyst's annual one-year-ahead earnings forecast.
FREQ	Number of an analyst's one-year-ahead earnings forecasts issued for the firm's preceding fiscal year.
GEXP	An analyst's general experience. It is measured as the number of years the analyst has appeared in I/B/E/S up to the preceding fiscal year.
HM_CONSV	An analyst's relative conservatism measure introduced by Hugon and Muslu (2010). *HM_CONSV* is the quintile rank of an analyst's conservatism score measured in the preceding fiscal year. An analyst's conservatism score is $(\beta_0+\beta_1)/\beta_0$ from Equation (1) of Hugon and Muslu (2010).
HORIZON	Forecast horizon. It is defined as the number of days between the analyst's earnings forecast date and the earnings announcement date.
MATCH$^{L\ (\text{or}\ C)}$	The measure of an analyst expertise in matching the analyst's asymmetric forecast timeliness with a firm's asymmetric earnings timeliness. It is measured by the absolute difference between *Analyst.ATC* and *Firm.ATC*$^{L\ (\text{or}\ C)}$, multiplied by -1: $MATCH^{L\ (\text{or}\ C)} = -1 \times \lvert Analyst.ATC - Firm.ATC^{L\ (\text{or}\ C)} \rvert$.
NFIRM	Number of firms an analyst covered in the preceding fiscal year.
NIND	Number of industries an analyst covered in the preceding fiscal year.
Promotion	An indicator that is equal to one if an analyst moves from a low-status to a high-status brokerage house in the following year. A brokerage house with more than 25 analysts is defined as a high-status brokerage house.
RET	The market-adjusted, buy-and-hold returns between the prior forecast date and the current forecast date of an analyst. Return data is obtained from the CRSP Daily File. The two forecasts are annual earnings forecasts for the same firm and fiscal year.
RET^{Annual}	A firm's market-adjusted, buy-and-hold returns from nine months before its fiscal year-end to three months after its fiscal year-end (Basu, 1997).

Appendix continued

Variable	Description
RetVolatility	Standard deviation of monthly stock returns of a firm during the past 12 months relative to an analyst's annual earnings forecast date.
REV	An analyst's one-year-ahead earnings forecast revision. It is the difference between the two consecutive (current and immediately preceding) earnings forecasts of the analyst for the same firm and fiscal year, scaled by the closing stock price on the last trading day of the month of the immediately preceding forecast.
SIZE	Natural logarithm of the firm's market value of equity at the end of the preceding fiscal year.
Stay in Profession	An indicator that is equal to one if an analyst remains on I/B/E/S in the following year.
Turnover	An indicator that is equal to one if an analyst moves from one brokerage house to another on I/B/E/S, leaves the profession, or moves to another brokerage house not included on I/B/E/S in the following year.
3-Month/6-Month/1-year Profitability	The market-adjusted buy-and-hold returns to a stock recommendation made by an analyst for a firm. The abnormal returns are calculated over the period starting from the day before the recommendation date until the earlier of 3/6/12 months or two days before the recommendation is revised or reiterated.

Figure 1
A Real-Life Example: EPS Forecasts, Performance, and Timeliness-Matching Ability of Two Different Analysts

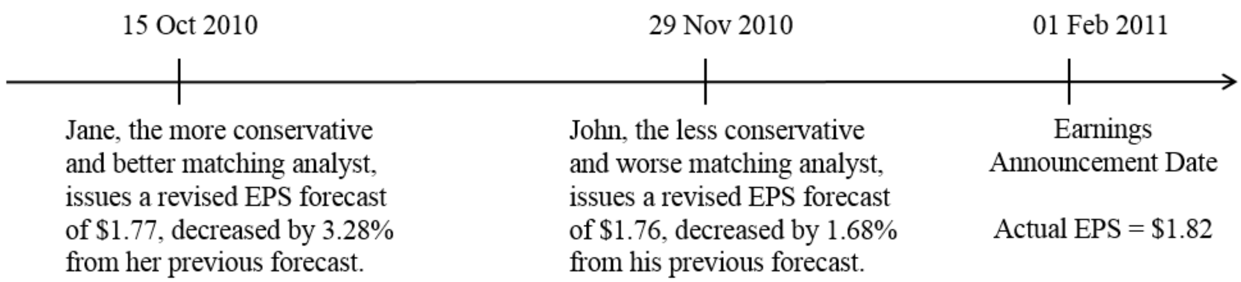
Panel A: When following an aggressive (i.e., low conservatism) firm



Company Name: Union Pacific Corp.	Jane Doe	John Doe
The level of asymmetric forecast timeliness:	-0.072	0.150
(*Analyst.ATC*)	(less conservative)	(more conservative)
The level of asymmetric earnings timeliness: ($Firm.ATC^L$)	-0.015	-0.015
The degree of matching two asymmetric timeliness:	-0.057	-0.165
$MATCH^L = -1\times\lvert Analyst.ATC - Firm.ATC^L\rvert$	(better match)	(worse match)
Absolute forecast error:	$0.035	$0.080
AFE = |*Actual EPS* – *Forecasted EPS*|	(more accurate)	(less accurate)
Absolute market reaction to forecast revision:	1.743%	1.012%
|*CAR* (-1, +1)| around the forecast revision date	(stronger reaction)	(weaker reaction)

Figure 1 continued

Panel B: When following a conservative (i.e., high conservatism) firm



Company Name: Landstar System, Inc.	Jane Doe	John Doe
The level of asymmetric forecast timeliness:	0.027	-0.001
(*Analyst.ATC*)	(more conservative)	(less conservative)
The level of asymmetric earnings timeliness: ($Firm.ATC^L$)	0.069	0.069
The degree of matching two asymmetric timeliness:	-0.042	-0.070
$MATCH^L = -1\times\lvert Analyst.ATC - Firm.ATC^L\rvert$	(better match)	(worse match)
Absolute forecast error:	$0.050	$0.060
AFE = |*Actual EPS – Forecasted EPS*|	(more accurate)	(less accurate)
Absolute market reaction to forecast revision:	4.157%	2.960%
|*CAR* (-1, +1)| around the forecast revision date	(stronger reaction)	(weaker reaction)

Table 1

Summary Statistics for Firms' Asymmetric Earnings Timeliness, Analysts' Asymmetric Forecast Timeliness, and Analysts' Timeliness Match

Panel A: Firms' asymmetric earnings timeliness based on Equation (1a), *Firm.ATC*^{L}

Parameter estimates	N	Mean	Lower quartile	Median	Upper quartile	Std. Dev.
RET^{Annual}	7,574	0.004***	-0.017	0.001***	0.026	0.069
$RET^{Annual} \times D$ (*Firm.ATC*^{L})	7,574	0.016***	-0.035	0.009***	0.059	0.132
$RET^{Annual} + RET^{Annual} \times D$	7,574	0.019***	-0.021	0.012***	0.050	0.105

Panel B: Firms' asymmetric earnings timeliness based on Equation (1b), *Firm.ATC*^{C}

Parameter estimates	N	Mean	Lower quartile	Median	Upper quartile	Std. Dev.
RET^{Annual}	6,792	0.007***	-0.006	0.002***	0.019	0.064
$RET^{Annual} \times D$ (*Firm.ATC*^{C})	6,792	0.011***	-0.019	0.005***	0.038	0.110
$RET^{Annual} + RET^{Annual} \times D$	6,792	0.018***	-0.008	0.008***	0.036	0.089

Panel C: Analysts' asymmetric forecast timeliness based on Equation (2), *Analyst.ATC*

Parameter estimates	N	Mean	Lower quartile	Median	Upper quartile	Std. Dev.
RET	27,092	0.007***	-0.003	0.003***	0.015	0.046
$RET \times D$ (*Analyst.ATC*)	27,092	0.005***	-0.012	0.002***	0.021	0.072
$RET + RET \times D$	27,092	0.013***	-0.003	0.005***	0.023	0.053

Panel D: Match between a firm's asymmetric earnings timeliness and an analyst's asymmetric forecast timeliness for the firm based on Equation (3), $MATCH^{L(\text{or } C)}$

Parameter estimates	N	Mean	Lower quartile	Median	Upper quartile	Std. Dev.
$MATCH^L$	27,092	-0.093***	-0.119	-0.055***	-0.023	0.110
$MATCH^C$	24,747	-0.073***	-0.090	-0.035***	-0.012	0.100

This table presents summary statistics for the parameter estimates from the 7,574 firm-year regressions of Equation (1a) in Panel A, the parameter estimates from the 6,792 firm-year regressions of Equation (1b) in Panel B, and the parameter estimates from the 27,092 analyst-firm-year regressions of Equation (2) in Panel C. In Panel D, we report summary statistics for analyst-firm-year measures of timeliness-matching ability. All parameter estimates are winsorized at the 1% and 99% levels. See the Appendix for variable definitions. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

Table 2

Summary Statistics for Analyst, Firm, and Forecast Characteristics

Variable	Mean	Lower quartile	Median	Upper quartile	Std. Dev.
REV	-0.001	-0.003	0.000	0.002	0.012
ACCURACY	-0.012	-0.011	-0.004	-0.001	0.029
Forecast Optimism	0.003	-0.004	0.000	0.004	0.027
CAR (-1, +1)	0.000	-0.030	0.000	0.031	0.064
HM_CONSV	3.059	2	3	4	1.390
FEXP	6.5	4	6	8	3.3
GEXP	10.0	6	9	13	5.0
NFIRM	18.4	13	17	21	8.3
NIND	3.7	2	3	5	2.3
BSIZE	71.0	25	60	120	53.4
FREQ	7.0	5	6	9	3.3
HORIZON	175.8	104	184	251	86.1
DaysElapsed	8.8	1	3	9	15.3
BM	0.464	0.252	0.389	0.584	0.319
SIZE	15.458	14.320	15.439	16.547	1.592
RetVolatility	0.111	0.071	0.098	0.135	0.059
EarnQuality	-0.028	-0.034	-0.023	-0.015	0.021
AvgAccuracy	-0.009	-0.010	-0.005	-0.002	0.014
AvgFE	-0.002	-0.003	0.000	0.001	0.011

This table presents summary statistics for analyst, firm, and forecast-specific characteristics in the sample of 116,284 firm-year, analyst-forecast horizons between 1998 and 2010. All continuous variables are winsorized at the 1% and 99% levels. See the Appendix for variable definitions.

Table 3
The Association of Timeliness Match with Analyst-, Forecast- and Firm-specific Characteristics

Panel A: Summary statistics by *MATCH*^{L} quintiles

	MATCH^L Quintiles					
	1 (worst)	2	3	4	5 (best)	
	N=5,418	*N*=5,419	*N*=5,418	*N*=5,419	*N*=5,418	*t*-test
Mean value of *MATCH*^{L}	-0.269	-0.103	-0.056	-0.029	-0.009	(Wilcoxon *z*)
			Mean (Median)			
Firm.ATC^L	0.054	0.024	0.013	0.006	0.004	-14.62***
	(0.088)	(0.049)	(0.026)	(0.009)	(0.004)	(-15.88)***
Analyst.ATC	0.008	0.007	0.005	0.004	0.004	-2.11**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.68)
HM_CONSV	3.03	3.03	3.04	3.06	3.06	1.15
	(3.00)	(3.00)	(3.00)	(3.00)	(3.00)	(1.13)
FEXP	6.31	6.68	6.89	7.00	6.94	10.05***
	(6.00)	(6.00)	(6.00)	(6.00)	(6.00)	(11.18)***
GEXP	9.81	10.31	10.32	10.43	10.32	5.34***
	(9.00)	(9.00)	(9.00)	(10.00)	(9.00)	(6.21)***
NFIRM	18.95	18.47	18.29	18.47	18.84	-0.63
	(17.00)	(17.00)	(17.00)	(17.00)	(17.00)	(-0.01)
NIND	3.78	3.85	3.80	3.94	3.99	4.43***
	(3.00)	(3.00)	(3.00)	(3.00)	(4.00)	(5.37)***
BSIZE	68.63	69.13	69.13	71.43	69.80	1.15
	(59.00)	(57.00)	(56.00)	(59.00)	(59.00)	(1.43)
FREQ	6.27	5.99	5.87	5.79	5.74	-9.60***
	(6.00)	(5.00)	(5.00)	(5.00)	(5.00)	(-7.84)***
Avg (*HORIZON*)	175.62	174.10	175.31	171.14	172.78	-2.87***
	(177.45)	(175.25)	(175.71)	(172.92)	(174.80)	(-2.97)***
Avg (*DaysElapsed*)	10.95	10.78	9.72	10.10	9.75	-4.49***
	(5.33)	(5.20)	(5.00)	(5.25)	(5.20)	(-2.92)***
BM	0.56	0.47	0.43	0.40	0.39	-26.55***
	(0.48)	(0.40)	(0.36)	(0.34)	(0.32)	(-27.85)***
SIZE	14.97	15.33	15.50	15.56	15.46	15.96***
	(14.95)	(15.30)	(15.52)	(15.50)	(15.37)	(15.14)***
Avg (*RetVolatility*)	0.121	0.108	0.105	0.106	0.108	-11.47***
	(0.105)	(0.094)	(0.093)	(0.094)	(0.096)	(-9.18)***
EarnQuality	-0.030	-0.029	-0.029	-0.029	-0.029	3.79***
	(-0.024)	(-0.024)	(-0.024)	(-0.023)	(-0.025)	(0.24)
AvgAccuracy	-0.016	-0.009	-0.007	-0.006	-0.005	37.11***
	(-0.009)	(-0.005)	(-0.004)	(-0.003)	(-0.002)	(49.54)***
AvgFE	-0.005	-0.002	-0.001	-0.001	-0.001	17.06***
	(-0.001)	(-0.000)	(-0.000)	(-0.000)	(-0.000)	(14.25)***

Table 3 continued

Panel B: Summary statistics by $MATCH^{C}$ quintiles

	$MATCH^{C}$ Quintiles					
	1 (worst)	2	3	4	5 (best)	
	N=4,949	*N*=4,950	*N*=4,949	*N*=4,950	*N*=4,949	*t*-test
Mean value of $MATCH^{C}$	-0.233	-0.076	-0.036	-0.016	-0.005	(Wilcoxon *z*)
	Mean (Median)					
$Firm.ATC^{C}$	0.023	0.012	0.007	0.006	0.003	-6.70***
	(0.033)	(0.013)	(0.008)	(0.006)	(0.001)	(-9.98)***
Analyst.ATC	0.009	0.007	0.004	0.004	0.003	-2.83***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(-0.17)
HM_CONSV	3.02	3.02	3.07	3.04	3.03	0.32
	(3.00)	(3.00)	(3.00)	(3.00)	(3.00)	(0.31)
FEXP	6.01	6.51	6.83	7.10	7.36	20.89***
	(5.00)	(6.00)	(6.00)	(6.00)	(7.00)	(20.83)***
GEXP	9.50	10.07	10.34	10.52	10.83	13.20***
	(8.00)	(9.00)	(9.00)	(10.00)	(10.00)	(14.46)***
NFIRM	18.77	18.30	18.16	18.18	18.21	-3.27***
	(17.00)	(17.00)	(17.00)	(17.00)	(17.00)	(-4.48)***
NIND	3.63	3.87	3.98	3.88	3.85	4.65***
	(3.00)	(3.00)	(4.00)	(3.00)	(3.00)	(5.01)***
BSIZE	67.95	69.86	70.92	70.97	72.48	4.16***
	(55.00)	(57.50)	(57.00)	(60.00)	(60.00)	(4.78)***
FREQ	6.48	6.27	5.91	5.68	5.51	-17.16***
	(6.00)	(6.00)	(5.00)	(5.00)	(5.00)	(-16.00)***
Avg (*HORIZON*)	176.80	176.59	174.20	171.84	170.98	-5.58***
	(178.00)	(177.88)	(175.20)	(174.00)	(172.80)	(-5.80)***
Avg (*DaysElapsed*)	11.41	10.96	9.87	9.38	9.24	-7.86***
	(5.75)	(5.28)	(5.00)	(5.00)	(5.00)	(-6.59)***
BM	0.59	0.51	0.44	0.38	0.33	-40.59***
	(0.51)	(0.45)	(0.36)	(0.32)	(0.28)	(-41.72)***
SIZE	14.72	15.18	15.46	15.68	15.90	36.62***
	(14.65)	(15.13)	(15.46)	(15.63)	(15.84)	(33.84)***
Avg (*RetVolatility*)	0.130	0.113	0.106	0.101	0.097	-27.48***
	(0.113)	(0.099)	(0.094)	(0.089)	(0.086)	(-27.48)***
EarnQuality	-0.032	-0.030	-0.029	-0.028	-0.028	9.22***
	(-0.025)	(-0.024)	(-0.024)	(-0.023)	(-0.024)	(8.06)***
AvgAccuracy	-0.018	-0.010	-0.007	-0.004	-0.003	46.28***
	(-0.011)	(-0.006)	(-0.004)	(-0.003)	(-0.002)	(68.48)***
AvgFE	-0.005	-0.002	-0.001	-0.001	0.000	19.62***
	(-0.002)	(-0.001)	(-0.000)	(-0.000)	(0.000)	(22.64)***

Table 3 continued

Panel C: Regressions of timeliness match on analyst, forecast and firm characteristics				
Dependent variable:	$MATCH^L$		$MATCH^C$	
Variables	(1)	(2)	(3)	(4)
$Firm.ATC^L$	-0.171***	-0.158***		
	(-4.65)	(-4.64)		
$Firm.ATC^C$			-0.099	-0.071
			(-1.54)	(-1.24)
HM_CONSV	-0.534	-0.349	-0.970**	-0.664
	(-1.06)	(-0.86)	(-2.06)	(-1.61)
FEXP		2.765***		3.181***
		(4.51)		(4.94)
GEXP		-0.396		-0.305
		(-1.53)		(-1.51)
NFIRM		-0.411*		-0.486***
		(-1.93)		(-3.42)
NIND		1.570**		2.193***
		(2.04)		(3.62)
BSIZE		-0.014		0.002
		(-1.09)		(0.09)
FREQ		0.349		-0.347
		(0.87)		(-0.79)
Avg (*HORIZON*)		-0.004		0.005
		(-0.24)		(0.27)
Avg (*DaysElapsed*)		-0.067		0.008
		(-0.80)		(0.12)
BM		-0.021***		-0.030***
		(-3.78)		(-3.19)
SIZE		0.003**		0.006***
		(2.32)		(3.03)
Avg (*RetVolatility*)		0.094**		0.012
		(2.35)		(0.28)
EarnQuality		0.002		-0.068
		(0.02)		(-0.80)
AvgAccuracy		2.208***		2.299***
		(6.32)		(5.50)
AvgFE		-0.054		-0.458
		(-0.25)		(-1.53)
Constant	-0.067**	-0.128***	-0.076	-0.157***
	(-2.03)	(-3.58)	(-1.24)	(-3.80)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Number of observations	27,092	27,092	24,747	24,747
Adjusted R-squared	11.51%	19.98%	10.16%	23.40%

This table reports the relations between analyst, forecast, and firm characteristics and timeliness-matching performance. Panel A and Panel B present comparisons of means and medians of analyst, firm, and forecast characteristics across the quintiles of $MATCH^L$ and $MATCH^C$, respectively. Quintile 1 (5) corresponds to the worst (best) timeliness-matching analysts. *N* represents the number of analyst-firm-year observations for each quintile. Panel C presents results from the OLS regressions of timeliness match on analyst, firm, and forecast characteristics. The dependent variables are $MATCH^L$ and $MATCH^C$ in columns (1), (2) and (3), (4), respectively. See the Appendix for variable definitions. For ease of presentation, we multiply the coefficients on *HM_CONSV, FEXP, GEXP, NFIRM, NIND, BSIZE, FREQ, Avg* (*HORIZON*), *and Avg* (*DaysElapsed*) by 1,000. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by firm and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

Table 4

Forecast Accuracy and Timeliness-Matching Performance

Dependent variable: *ACCURACY*						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$MATCH^L$	0.031***	0.008**	0.007*			
	(5.90)	(2.11)	(1.86)			
$MATCH^C$				0.048***	0.014***	0.014***
				(5.68)	(3.75)	(3.79)
$Firm.ATC^L$			-0.003			
			(-1.10)			
$Firm.ATC^C$						-0.002
						(-0.32)
HM_CONSV			-0.028			-0.045
			(-0.31)			(-0.55)
FEXP		-0.236**	-0.233**		-0.241**	-0.240**
		(-2.13)	(-2.08)		(-2.05)	(-2.05)
GEXP		0.042	0.042		0.030	0.031
		(0.87)	(0.86)		(0.60)	(0.63)
NFIRM		0.016	0.015		0.035	0.033
		(0.44)	(0.42)		(0.91)	(0.91)
NIND		0.239**	0.234**		0.288***	0.293***
		(2.10)	(2.04)		(2.90)	(2.97)
BSIZE		-0.002	-0.002		-0.002	-0.002
		(-0.62)	(-0.64)		(-0.59)	(-0.57)
FREQ		-0.229**	-0.229**		-0.206*	-0.205*
		(-2.09)	(-2.12)		(-1.83)	(-1.84)
HORIZON		-0.055***	-0.055***		-0.055***	-0.055***
		(-11.69)	(-11.70)		(-11.21)	(-11.20)
DaysElapsed		0.002	0.002		0.002	0.002
		(0.11)	(0.09)		(0.09)	(0.09)
BM		-0.012***	-0.012***		-0.012***	-0.012***
		(-2.65)	(-2.67)		(-2.61)	(-2.60)
SIZE		0.001***	0.001***		0.001**	0.001**
		(2.69)	(2.66)		(2.48)	(2.50)
RetVolatility		-0.076***	-0.075***		-0.074***	-0.074***
		(-4.46)	(-4.46)		(-4.02)	(-4.00)
EarnQuality		0.003	0.002		0.010	0.010
		(0.29)	(0.21)		(0.82)	(0.78)
AvgAccuracy		0.361***	0.360***		0.340***	0.339***
		(3.94)	(3.92)		(3.51)	(3.51)
AvgFE		0.136**	0.137**		0.148***	0.148***
		(2.47)	(2.44)		(2.73)	(2.72)
Constant	0.005	0.004	0.004	-0.006*	-0.001	-0.001
	(0.95)	(0.61)	(0.67)	(-1.75)	(-0.15)	(-0.15)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	116,284	116,284	116,284	106,503	106,503	106,503
Adjusted R-squared	9.74%	24.80%	24.82%	11.52%	25.28%	25.28%

This table presents the results from the OLS regressions based on 116,284 (106,503) firm-year, analyst-forecast horizons from 1998 (1999) to 2010 in columns (1) to (3) [(4) to (6)]. The dependent variable is *ACCURACY*. See the Appendix for variable definitions. For ease of presentation, we multiply the coefficients on *HM_CONSV, FEXP, GEXP, NFIRM, NIND, BSIZE, FREQ, HORIZON*, and *DaysElapsed* by 1,000. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by firm and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.

Table 5

Market Reactions to Forecast Revisions and Timeliness-Matching Performance

Dependent variable: *CAR (-1, +1)*						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
REV×MATCH^L	1.715***	0.922***	0.919***			
	(4.44)	(4.30)	(4.77)			
REV×MATCH^C				2.000***	1.564***	1.551***
				(5.76)	(6.33)	(6.40)
REV	1.536***	5.086***	4.817***	1.561***	5.489***	5.229***
	(8.39)	(6.68)	(6.32)	(9.56)	(7.44)	(7.04)
MATCH^L	0.009**	0.008***	0.008**			
	(2.38)	(2.67)	(2.53)			
MATCH^C				0.007*	0.007**	0.008**
				(1.86)	(2.25)	(2.36)
REV×Firm.ATC^L			0.030			
			(0.36)			
REV×Firm.ATC^C						0.098
						(0.59)
REV×HM_CONSV			0.077***			0.071***
			(9.96)			(8.75)
REV×FEXP		-0.004	-0.003		-0.005	-0.004
		(-0.26)	(-0.25)		(-0.36)	(-0.33)
REV×GEXP		-0.005	-0.004		-0.012	-0.012*
		(-0.66)	(-0.58)		(-1.62)	(-1.71)
REV×NFIRM		-0.035***	-0.034***		-0.028***	-0.027***
		(-5.24)	(-4.81)		(-5.31)	(-5.17)
REV×NIND		0.070*	0.063*		0.061*	0.053
		(1.94)	(1.71)		(1.75)	(1.53)
REV×BSIZE		0.002***	0.002***		0.002**	0.001**
		(3.28)	(2.99)		(2.53)	(2.22)
REV×FREQ		-0.054***	-0.056***		-0.056***	-0.057***
		(-4.93)	(-5.21)		(-4.61)	(-4.81)
REV×HORIZON		0.000	0.000		0.000	0.001
		(0.61)	(0.63)		(1.38)	(1.40)
REV×DaysElapsed		0.002	0.002		0.002	0.002
		(1.15)	(1.26)		(1.27)	(1.36)
REV×BM		-0.550***	-0.557***		-0.510***	-0.516***
		(-2.78)	(-2.84)		(-2.82)	(-2.85)
REV×SIZE		-0.125***	-0.122***		-0.151***	-0.148***
		(-2.70)	(-2.65)		(-3.46)	(-3.41)
REV×RetVolatility		-2.967***	-2.983***		-2.774***	-2.787***
		(-7.94)	(-8.33)		(-8.05)	(-8.79)
REV×EarnQuality		-0.037	0.065		0.132	0.256
		(-0.02)	(0.03)		(0.06)	(0.11)
REV×AvgAccuracy		10.352***	10.526***		11.433***	11.605***
		(4.04)	(4.13)		(4.62)	(4.74)
REV×AvgFE		-1.999	-2.458		-1.944	-2.326
		(-1.06)	(-1.22)		(-1.02)	(-1.17)
Firm.ATC^L			-0.001			
			(-0.42)			
Firm.ATC^C						0.005**
						(2.17)
HM_CONSV			-0.159			-0.206
			(-0.83)			(-1.12)
FEXP		-0.104	-0.100		-0.128	-0.130
		(-1.01)	(-0.98)		(-1.25)	(-1.27)
GEXP		0.085*	0.081		0.098*	0.091*
		(1.67)	(1.58)		(1.93)	(1.80)
NFIRM		0.053	0.056		0.052	0.057
		(1.22)	(1.30)		(1.02)	(1.16)

NIND		-0.151	-0.158		-0.198	-0.210
		(-0.74)	(-0.79)		(-0.84)	(-0.92)
BSIZE		-0.007	-0.007		-0.008	-0.008
		(-1.47)	(-1.46)		(-1.56)	(-1.55)
FREQ		0.068	0.068		0.144	0.138
		(0.65)	(0.65)		(1.44)	(1.40)
HORIZON		0.007	0.007		0.006	0.006
		(1.03)	(1.02)		(0.95)	(0.94)
DaysElapsed		0.006	0.006		0.008	0.008
		(0.30)	(0.31)		(0.43)	(0.45)
BM		0.001	0.001		0.001	0.001
		(0.92)	(0.95)		(0.57)	(0.62)
SIZE		-0.324	-0.326		-0.401	-0.392
		(-1.03)	(-1.03)		(-1.21)	(-1.17)
RetVolatility		0.028*	0.028*		0.027*	0.027*
		(1.94)	(1.94)		(1.81)	(1.83)
EarnQuality		0.031	0.031		0.043	0.044
		(1.08)	(1.09)		(1.52)	(1.61)
AvgAccuracy		0.057	0.057		0.065	0.068
		(1.47)	(1.46)		(1.51)	(1.59)
AvgFE		-0.033	-0.031		-0.023	-0.023
		(-0.73)	(-0.69)		(-0.51)	(-0.51)
Constant	-0.027***	-0.024***	-0.023***	-0.014***	-0.009	-0.008
	(-6.67)	(-3.07)	(-3.02)	(-15.33)	(-1.42)	(-1.26)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	116,284	116,284	116,284	106,503	106,503	106,503
Adjusted *R*-squared	6.19%	7.54%	7.58%	6.40%	7.80%	7.84%

This table presents the results from the OLS regressions based on 116,284 (106,503) firm-year, analyst-forecast horizons from 1998 (1999) to 2010 in columns (1) to (3) [(4) to (6)]. The dependent variable is *CAR* (-1, +1). See the Appendix for variable definitions. For ease of presentation, we multiply the coefficients on *HM_CONSV, FEXP, GEXP, NFIRM, NIND, BSIZE, FREQ, HORIZON, DaysElapsed,* and *SIZE* by 1,000. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by firm and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.

Table 6

Overall Timeliness-Matching Ability across Firms

Panel A: Forecast Accuracy Test (H1)

Dependent Variable: *ACCURACY*						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Mean of $MATCH^L$	0.045***	0.013**	0.012*			
	(6.549)	(2.022)	(1.884)			
Mean of $MATCH^C$				0.059***	0.014**	0.014**
				(6.022)	(2.321)	(2.335)
Controls	Identical to the corresponding column in Table 4					
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	116,284	116,284	116,284	106,503	106,503	106,503
Adjusted *R*-squared	9.17%	24.79%	24.82%	10.25%	25.15%	25.16%

Panel B: Market Reactions to Forecast Revision Test (H2)

Dependent Variable: *CAR* (*-1, +1*)						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
REV×Mean of $MATCH^L$	3.798***	2.163***	2.176***			
	(8.263)	(5.108)	(4.878)			
REV×Mean of $MATCH^C$				4.233***	3.277***	3.235***
				(6.494)	(5.558)	(5.529)
Controls	Identical to the corresponding column in Table 5					
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	116,284	116,284	116,284	106,503	106,503	106,503
Adjusted *R*-squared	6.33%	7.57%	7.61%	6.48%	7.83%	7.87%

This table presents the results from the OLS regressions based on 116,284 (106,503) firm-year, analyst-forecast horizons from 1998 (1999) to 2010 in columns (1) to (3) [(4) to (6)]. The dependent variables are *ACCURACY* and *CAR* (*-1, +1*) in Panel A and Panel B, respectively. See the Appendix for variable definitions. *Mean of* (·) is a function that takes the mean value of the variable in parentheses at the analyst-year level. Control variables in Panel A and Panel B are identical to those in the corresponding column of Table 4 and Table 5, respectively. Intercept and control variables are suppressed for brevity. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by firm and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.

Table 7
Forecast Bias and Timeliness-Matching Performance

Dependent variable: *Forecast Optimism*						
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$MATCH^L$	-0.017***	-0.009***	-0.009***			
	(-4.42)	(-3.20)	(-3.04)			
$MATCH^C$				-0.019***	-0.007*	-0.007*
				(-2.96)	(-1.81)	(-1.91)
$Firm.ATC^L$			0.001			
			(0.36)			
$Firm.ATC^C$						-0.000
						(-0.05)
HM_CONSV			-0.074			-0.063
			(-0.56)			(-0.44)
FEXP		0.067	0.066		0.069	0.068
		(0.68)	(0.67)		(0.74)	(0.74)
GEXP		-0.006	-0.007		-0.014	-0.015
		(-0.13)	(-0.15)		(-0.33)	(-0.33)
NFIRM		-0.029	-0.029		-0.035	-0.036
		(-0.81)	(-0.82)		(-0.97)	(-0.99)
NIND		0.120	0.124		0.063	0.066
		(1.02)	(1.05)		(0.49)	(0.50)
BSIZE		-0.001	-0.001		-0.002	-0.002
		(-0.26)	(-0.23)		(-0.50)	(-0.48)
FREQ		0.080	0.081		0.063	0.063
		(0.66)	(0.67)		(0.44)	(0.45)
HORIZON		0.019**	0.019**		0.018**	0.018**
		(2.47)	(2.47)		(2.18)	(2.18)
DaysElapsed		-0.003	-0.003		-0.006	-0.006
		(-0.30)	(-0.29)		(-0.51)	(-0.51)
BM		0.009**	0.009**		0.009**	0.009**
		(2.48)	(2.45)		(2.24)	(2.23)
SIZE		-0.000	-0.000		-0.000*	-0.000*
		(-1.56)	(-1.55)		(-1.67)	(-1.70)
RetVolatility		0.017	0.017		0.015	0.015
		(0.96)	(0.96)		(0.81)	(0.81)
EarnQuality		-0.036**	-0.036**		-0.044**	-0.044**
		(-2.03)	(-2.02)		(-2.33)	(-2.36)
AvgAccuracy		-0.041	-0.041		-0.033	-0.033
		(-1.04)	(-1.04)		(-0.77)	(-0.75)
AvgFE		-0.135*	-0.135*		-0.129*	-0.129*
		(-1.80)	(-1.79)		(-1.77)	(-1.76)
Constant	-0.004	-0.004	-0.004	0.001	-0.000	-0.000
	(-0.64)	(-0.45)	(-0.42)	(0.10)	(-0.02)	(-0.01)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	116,284	116,284	116,284	106,503	106,503	106,503
Adjusted R-squared	5.92%	8.76%	8.76%	6.08%	8.68%	8.68%

This table presents the results from the OLS regressions based on 116,284 (106,503) firm-year, analyst-forecast horizons from 1998 (1999) to 2010 in columns (1) to (3) [(4) to (6)]. The dependent variable is *Forecast Optimism*. See the Appendix for variable definitions. For ease of presentation, we multiply the coefficients on *HM_CONSV, FEXP, GEXP, NFIRM, NIND, BSIZE, FREQ, HORIZON*, and *DaysElapsed* by 1,000. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by firm and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.

Table 8

Stock Recommendation Profitability and Timeliness-Matching Performance

Dependent variable:	*3-Month Profitability*		*6-Month Profitability*		*1-Year Profitability*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
MATCH^{L}	0.048**		0.075**		0.103**	
	(2.10)		(2.35)		(2.52)	
MATCH^{C}		0.043		0.114**		0.144**
		(1.25)		(2.15)		(2.49)
Firm.ATC^{L}	-0.007		-0.016		0.011	
	(-0.42)		(-0.70)		(0.33)	
Firm.ATC^{C}		0.038		0.059		0.083
		(1.30)		(1.61)		(1.63)
HM_CONSV	0.002	0.001	0.003*	0.002	0.000	-0.002
	(1.44)	(0.83)	(1.67)	(1.34)	(0.02)	(-0.78)
FEXP	-0.001	-0.001	-0.001*	-0.001	-0.001	-0.001
	(-0.84)	(-0.84)	(-1.73)	(-1.56)	(-0.82)	(-0.48)
GEXP	0.001	0.001	0.001**	0.001**	0.002	0.002
	(1.32)	(1.59)	(1.98)	(2.35)	(1.57)	(1.59)
NFIRM	-0.001**	-0.001**	-0.001***	-0.001**	-0.002**	-0.002**
	(-2.05)	(-2.42)	(-2.58)	(-2.35)	(-2.47)	(-2.47)
NIND	-0.637	-0.483	-0.405	-0.457	-1.610	-1.365
	(-0.67)	(-0.62)	(-0.46)	(-0.39)	(-0.88)	(-0.68)
BSIZE	0.041**	0.042**	0.071	0.057	0.054	0.021
	(2.31)	(2.17)	(1.39)	(1.02)	(0.66)	(0.24)
FREQ	0.583	0.149	0.434	0.052	-0.204	-0.515
	(0.93)	(0.22)	(0.54)	(0.06)	(-0.15)	(-0.35)
BM	0.029***	0.029***	0.028***	0.030***	0.013	0.008
	(3.66)	(3.77)	(2.88)	(2.73)	(0.62)	(0.44)
SIZE	-0.009***	-0.010***	-0.014***	-0.017***	-0.020***	-0.023***
	(-3.54)	(-4.07)	(-3.83)	(-4.18)	(-3.39)	(-4.17)
EarnQuality	-0.119	-0.009	-0.053	0.124	0.113	0.300
	(-0.69)	(-0.05)	(-0.26)	(0.63)	(0.44)	(1.07)
AvgAccuracy	-0.373*	-0.399**	-0.242	-0.180	-0.124	0.066
	(-1.75)	(-2.11)	(-0.64)	(-0.49)	(-0.28)	(0.18)
AvgFE	0.170	0.226	0.197	0.230	0.547	0.506
	(0.68)	(0.82)	(0.57)	(0.62)	(0.86)	(0.81)
Constant	0.209***	0.204***	0.306***	0.394***	0.514***	0.602***
	(3.31)	(4.75)	(2.64)	(3.55)	(3.44)	(5.73)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	11,344	10,335	11,344	10,335	11,344	10,335
Adjusted *R*-squared	1.81%	2.13%	2.39%	3.05%	1.93%	2.47%

This table presents the results from the OLS regressions based on 11,344 (10,335) firm-year, analyst-recommendations from 1998 (1999) to 2010 in columns (1), (3), and (5) [(2), (4), and (6)]. The dependent variables are *3-Month Profitability* in columns (1) and (2), *6-Month Profitability* in columns (3) and (4), and *1-Year Profitability* in columns (5) and (6). See the Appendix for variable definitions. For ease of presentation, we multiply the coefficients on *NIND*, *BSIZE*, and *FREQ* by 1,000. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by firm and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.

Table 9
Career Outcomes and Timeliness-Matching Performance

Dependent variable:	*Turnover*		*Stay in Profession*		*Promotion*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Mean of $MATCH^L$	-0.688*		0.731*		2.392	
	(-1.77)		(1.85)		(0.95)	
Mean of $MATCH^C$		-1.162*		1.239*		2.101
		(-1.88)		(1.79)		(1.38)
HM_CONSV	-0.052***	-0.046***	0.052***	0.047***	0.119	0.134
	(-3.02)	(-3.05)	(3.60)	(3.61)	(1.48)	(1.60)
GEXP	0.002	0.004	-0.004	-0.008	-0.004	-0.003
	(0.48)	(0.93)	(-0.78)	(-1.48)	(-0.19)	(-0.16)
NFIRM	0.003	0.003	-0.001	0.000	0.050**	0.043*
	(0.90)	(0.68)	(-0.18)	(0.00)	(2.27)	(1.88)
NIND	-0.097***	-0.099***	0.088**	0.093**	-0.156	-0.122
	(-3.34)	(-3.26)	(2.05)	(2.06)	(-1.54)	(-1.23)
BSIZE	0.000	0.000	-0.001***	-0.001***	-0.033***	-0.034***
	(0.14)	(0.08)	(-2.89)	(-2.63)	(-4.35)	(-3.81)
Mean of AvgAccuracy	-4.925*	-2.783	4.511*	1.713	-2.210	-2.945
	(-1.94)	(-0.78)	(1.66)	(0.48)	(-0.19)	(-0.27)
Mean of AvgFE	4.407	3.917	-3.485	-2.974	13.107	7.806
	(1.40)	(1.11)	(-1.40)	(-0.97)	(0.78)	(0.40)
Constant	-5.008***	-0.548***	5.074***	0.665***	-2.259***	-2.311***
	(-21.84)	(-5.74)	(20.52)	(4.57)	(-5.60)	(-5.72)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	7,663	7,096	7,663	7,096	667	638
Pseudo *R*-squared	6.33%	5.78%	8.54%	8.18%	34.39%	33.71%

This table presents the results from the probit regressions based on 7,663 (7,096) analyst-years from 1998 (1999) to 2010 in columns (1) and (3) [(2) and (4)]. Columns (5) and (6) present the results from the probit regressions based on 667 and 638 analyst-years which have a value of one for *Turnover.* The dependent variables are *Turnover, Stay in Profession*, and *Promotion* in columns (1) and (2), (3) and (4), and (5) and (6), respectively. See the Appendix for variable definitions. *Mean of* (·) is a function that takes the mean value of the variable in parentheses at the analyst-year level. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by analyst and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.

Table 10

Matching Expertise in Gain and Loss Timeliness

Panel A: Forecast Accuracy Test (H1)

Dependent variable: *ACCURACY*

Variables	(1)	(2)	(3)	(4)	(5)	(6)
GAIN_MATCH^L	0.022***					
	(3.49)					
LOSS_MATCH^L		0.010***				
		(2.93)				
AVG_GL_MATCH^L			0.025***			
			(3.64)			
GAIN_MATCH^C				0.025***		
				(3.73)		
LOSS_MATCH^C					0.010***	
					(2.84)	
AVG_GL_MATCH^C						0.026***
						(3.73)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	116,284	116,284	116,284	106,503	106,503	106,503
Adjusted *R*-squared	24.95%	24.85%	24.98%	25.30%	25.17%	25.30%

Panel B: Market Reactions to Forecast Revisions Test (H2)

Dependent variable: *CAR* (*-1, +1*)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
REV×*GAIN_MATCH*^{L}	1.409***					
	(4.16)					
REV×*LOSS_MATCH*^{L}		1.512***				
		(7.11)				
REV×*AVG_GL_MATCH*^{L}			2.713***			
			(8.67)			
REV×*GAIN_MATCH*^{C}				2.313***		
				(7.13)		
REV×*LOSS_MATCH*^{C}					1.811***	
					(5.48)	
REV×*AVG_GL_MATCH*^{C}						3.512***
						(7.29)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls interacted with *REV*	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	116,284	116,284	116,284	106,503	106,503	106,503
Adjusted *R*-squared	7.57%	7.64%	7.67%	7.82%	7.83%	7.91%

This table presents the results from the OLS regressions based on 116,284 (106,503) firm-year, analyst-forecast horizons from 1998 (1999) to 2010 in columns (1) to (3) [(4) to (6)]. The dependent variables are *ACCURACY* and *CAR* (*-1, +1*) in Panel A and Panel B, respectively. See the Appendix for variable definitions. Control variables in Panel A and Panel B are identical to those in column (3) of Table 4 and Table 5, respectively. Intercept and control variables are suppressed for brevity. In parentheses below coefficient estimates are robust *t*-statistics based on standard errors clustered by firm and year (Petersen, 2009). All continuous variables are winsorized at the 1% and 99% levels. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% level, respectively.