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The coverage assignments of financial analysts

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Previous studies document that forecast accuracy impacts analyst career outcomes. This paper investigates the influence of forecast accuracy on coverage assignments. I show that brokerage houses reward accurate analysts by assigning them to high-profile firms and penalise analysts exhibiting poor accuracy by assigning them to smaller firms. The coverage of high-profile firms increases the potential for future compensation linked to investment banking and trading commissions. In addition, covering such firms increases analysts' recognition from buy-side investors, which, in turn, increases the likelihood of obtaining broker votes and votes for the *Institutional Investor* star ranking. Overall, my results indicate that high forecast accuracy leads to increased future compensation.

Keywords: financial analysts; career concerns; forecast accuracy; coverage decisions

1. Introduction

Analysts play a key role in disseminating information in capital markets. They also represent a good proxy for beliefs held by investors (Ivkovic and Jegadeesh 2004). In view of this important role played within the financial market, numerous studies in finance and accounting have investigated the behaviour of financial analysts. A key issue in the study of analysts' behaviour is the existence of potential conflicts of interest and incentives to strategically bias earnings forecasts and recommendations. A large body of literature therefore focuses on analysis of these conflicts of interest (Lin and McNichols 1998; Michaely and Womack 1998; O'Brien et al. 2005; Cowen et al. 2006; Ljungqvist et al. 2006). Other studies investigate career-based incentives that counteract conflicts of interest. A number of papers document a link between earnings forecast accuracy (commonly used as a proxy for analyst quality) and career outcomes. Mikhail et al. (1999) and Hong and Kubik (2003) show that analysts who are relatively inaccurate tend to experience higher job turnover and are more likely to be laid

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off, while accurate forecasters have better chances to move up to high-status brokerage houses. Emery and Li (2009) find empirical evidence that forecast accuracy has an impact, albeit a small one, on the likelihood of being an *Institutional Investor* (I/I) star analyst. Finally, Brown et al. (2015) report that 35% of surveyed analysts consider earnings forecast accuracy to be a very important determinant of their compensation.

In this paper, I investigate another channel through which forecast accuracy matters for career outcomes. The study focuses on the relationship between forecast accuracy and analyst coverage assignments by testing whether accurate forecasters are more likely to cover high-profile firms than their counterparts. In doing so, I assume that analysts do not have complete discretion over which firms they cover. Most of the analysts surveyed by Brown et al. (2015, p. 41) said 'they are required to run their coverage decisions through their firm's research management'. Financial analysts compete over the coverage of high-profile firms since the rewards of covering such firms are much greater than the rewards of covering small firms. First, these firms have greater investor recognition (especially from large buy-side investors) and attract substantial media attention for the analysts covering them. Covering high-profile firms increases analyst recognition and increases the likelihood of obtaining broker votes and votes for the I/I star ranking (Emery and Li 2009 find that covering larger firms increases the likelihood of being an I/I star).[1] Second, as high-profile firms have large market capitalisation and high trading volume, their coverage leads to potentially higher underwriting business[2] and trading commissions. (Groysberg et al. 2011 indicate that two of the four main factors that explain variations in analyst compensations are an analyst's investment banking contributions and the market capitalisation of the covered firms.) Although there is no empirical evidence of a direct link between forecast accuracy and compensation, accurate forecasters are likely to obtain future increases in compensation as a result of better stock coverage assignments.

This study uses a large dataset of analysts' earnings forecasts over the 1994–2014 period to examine how analysts' forecast accuracy influences the type of firms they cover. I begin by estimating the relationship between the likelihood that an analyst switches to larger firms and his/her past forecast accuracy. Conversely, I also investigate the impact of past forecast accuracy on the likelihood that an analyst moves to the coverage of smaller firms. While testing how forecast accuracy relates to the quality of coverage assignments, I also control for several analyst characteristics. The first of these is the experience of analysts; given the dynamics of the labour market, analysts tend to move up the brokerage house hierarchy as they gain experience, and experienced analysts are therefore more likely to cover high-profile firms. Recommendation profitability is also an important factor to consider, as described by Brown et al. (2015), who report that the primary motivation for issuing accurate earnings forecasts is to use them as an input for stock recommendations. In addition, Loh and Mian (2006) provide evidence that accurate forecasters tend to issue more profitable recommendations. It is important to disentangle the direct relationship between forecast accuracy and the quality of coverage assignments from the indirect relationship between the two via the profitability of stock recommendations. Other controls include a measure of forecast boldness, a measure of forecast optimism and the log number of firms covered.

The results indicate that being in the top 10% of forecast accuracy increases the likelihood of moving on to cover large firms by up to 12.71% (depending on the measure of forecast accuracy used). In contrast, analysts who are in the bottom 10% of forecast accuracy are 11.4% less likely to move on to cover larger firms than the other analysts. The influence of forecast accuracy is greater for switching to smaller firms. Being in the bottom decile of forecast accuracy increases the likelihood that an analyst switches to smaller firms (or is laid off) by up to 20%. While market capitalisation is a reasonable characteristic to qualify firms as high profile or low profile, I also consider trading volume. In terms of potential for commissions, firms with high trading volume may be more desirable for analysts to cover than large firms.[3] Following recent regulations aiming to separate research and investment banking in brokerage houses, incentives to generate investment banking business have been replaced with incentives to generate trading commissions (Jackson 2005; Brown et al. 2015). An analysis using trading volume as a proxy for firm type yields similar conclusions.

This first analysis thus establishes the link between forecast accuracy and coverage assignments. However, further analysis is needed to show that brokerage houses assign high-profile firms to accurate forecasters. Indeed, the relationship between past forecast accuracy and the coverage of high-profile firms could be explained by the greater likelihood of inaccurate forecasters being laid off. Accurate forecasters manage to remain in the profession (i.e. they do not get laid off) and gradually manage to cover high-profile firms. My second analysis employs a more direct approach to test whether brokerage houses reward accurate forecasters with better job assignments. I look at the initiation of coverage by brokerage firms and check whether the analyst who initiated the coverage for the brokerage house has superior forecasting skills. I also look at the importance of industry knowledge, as it is consistently ranked as the most important quality in *Institutional Investor* surveys of buy-side clients. Brown et al. (2015) also report that industry knowledge is an important determinant of financial analyst compensation. My results are consistent with these views: industry knowledge is the primary predictor for the choice of the analyst initiating coverage for a brokerage house.[4] Beyond the effect of industry knowledge, forecast accuracy appears to be another important factor to predict the selection of an analyst to initiate coverage. The influence of forecast accuracy is all the more striking for the coverage initiation of high-profile firms.

Overall, my empirical findings indicate that brokerage houses reward accurate forecasters by assigning them to cover high-profile firms. In contrast, analysts exhibiting poor accuracy are penalised and left with the coverage of smaller firms. While the literature does not provide explanations as to why brokerage houses care about accuracy, the more logical explanation is reputation risk. Inaccurate forecasts damage the reputation of brokerage houses (Jackson 2005; Fang and Yasuda 2009). As forecast accuracy is directly observable by buy-side investors and firm managers (even for market participants who do not have a commercial relationship with the brokerage house), it may be seen as a prerequisite for trusting the brokerage house (Bradshaw 2011). Indeed, Jackson (2005) shows that market participants assess the analyst reputations with respect to their end-of-period forecast accuracy. Damage to the reputation of a brokerage house reduces the potential for future revenues. However, evidence from *Institutional Investor* ranking surveys indicates that buy-side investors do not consider forecast accuracy to be important (Bradshaw 2011): earnings forecasts routinely rank in the lowest positions of analysts' traits that add value to buy-side investors. An alternative explanation for why brokerage houses care about forecast accuracy is that forecast accuracy may simply proxy for a much larger (and empirically unobservable) construct that relates to the quality of analysts. Brokerage houses reward accurate analysts because these analysts also add value in other ways, such as industry knowledge, relationships with company management and interactions with buy-side clients. Brokerage houses focus on the end result, that is, earnings forecasts, because contrary to the qualitative information provided by analysts in their reports, forecast accuracy can easily be assessed *ex post*.

The remainder of the paper is organised as follows: Section 2 provides a review of the literature. Section 3 presents the data and the different measures used in the paper. The empirical results are discussed in Section 4. Section 5 concludes.

2. Literature review

2.1. *Forecast accuracy and career concerns*

A primary incentive for analysts to issue accurate earnings forecasts is to use them as an input to their stock recommendations. Brown et al. (2015) indicate that more than 70% of the analysts they surveyed reported that their own earnings forecasts are a very useful input to their stock recommendations. Loh and Mian (2006) and Ertimur et al. (2007) show that analysts with more accurate earnings forecasts tend to issue more profitable stock recommendations.

Other incentives to issue accurate earnings forecasts are linked to career concerns. While there is no empirical evidence of a direct link between forecast accuracy and analysts' compensation,[5] several studies have shown that forecast accuracy has a significant impact on career outcomes. For instance, Mikhail et al. (1999) find a negative relationship between relative forecast accuracy and job turnover. Hong et al. (2000) find that young analysts are more likely than their older counterparts to be laid off for poor relative forecast accuracy and bold forecasts. Hong and Kubik (2003) show that analysts who issue less accurate forecasts are more likely to be laid off. They also find that relatively accurate forecasters tend to experience more favourable career outcomes, that is, to move up to a high-status brokerage house. Stickel (1992) and Emery and Li (2009) show that forecast accuracy is a significant determinant of being an I/I star.

Other studies document the existence of a trade-off between long-term benefits of analyst reputation and short-term incentives to issue biased research. Jackson (2005) investigates the conflict between issuing biased forecasts in order to generate short-term increases in trading commissions and producing accurate research to build a reputation. Similarly, Fang and Yasuda (2009) document the trade-off between an immediate increase in underwriting-related compensation and a long-term decrease in career prospects as a result of a diminished reputation. Both studies find that the long-term benefits of reputation exceed the short-term incentives of issuing biasing research. Dunbar (2000), Krigman et al. (2001), and Clarke et al. (2007) provide additional evidence that reputation concerns are critical for brokerage houses.

2.2. *Determinants of analyst coverage*

McNichols and O'Brien (1997) is one of the first papers to document the determinants of coverage choices. They find that analysts exhibit self-selection, adding firms that they view favourably and dropping firms that they view unfavourably. Barth et al. (2001) show that analysts' incentives to cover firms also relate to the level of intangibles assets. Firms with substantial intangible assets present more information asymmetry between managers and investors, leading to a higher level of uncertainty surrounding their valuation. As a result, these firms have less informative prices. This creates opportunities for analysts to acquire private information and leads them to issue more profitable investments recommendations; thus, they obtain higher trading commissions. More generally, incentives to cover firms are linked with the quality of public information: the better the information environment, the easier it is for an analyst to compile information and use it for issuing earnings forecasts and recommendations (O'Brien and Bushan 1990; Lang and Lundholm 1996; Graham 1999). Barth et al. (2001) also document that analyst coverage increases with the level of research and development and advertising, firm size, growth, trading volume, equity issuance, and perceived mispricing. The relationship between firm size and analyst coverage is confirmed by Ackert and Athanassakos (2003) and Leung and Srinidhi (2006). Li et al. (2009) study how analysts' career concerns affect their coverage choices and find that analysts strategically choose the firms they cover. Up-and-coming analysts (i.e. analysts who are about to be elected I/I stars) tend to stop covering firms with high absolute abnormal accruals and switch to low-earnings management firms. O'Brien and Tan (2015) investigate the impact of geographic proximity on analyst coverage decisions. Using data on analyst locations, they find that analysts are more likely to cover local firms than non-local firms.

Shon and Young (2011) study analysts' decisions to drop the coverage of firms. They relate their decisions to drop coverage to their economic incentives and to the accounting fundamentals of firms. The likelihood of dropping coverage decreases with trading volume, liquidity and market size and increases with firm risk. These different characteristics directly impact the analysts' incentives to continue covering a firm. The likelihood of dropping coverage is also linked with accounting fundamentals: accounting losses and decreasing gross margins increase the probability that an analyst will stop covering a firm. Shon and Young (2011) also document that the determinants of dropped coverage vary according to the analysts' experience. Less experienced analysts react more to increases in firm risk and decreases in liquidity, while the more experienced analysts are more sensitive to accounting losses and decreasing margins.

Overall, these different papers provide insightful input on analyst coverage determinants. However, they take coverage choice as a given. The present study differs from the previous literature as it assumes that coverage choices are somewhat constrained. Under the assumption that brokerage houses have an influence on the coverage decisions of financial analysts, it is important to study the underlying coverage attribution mechanisms. Financial analysts compete for the coverage of high-profile firms. This study is interested in understanding how brokerage houses determine these coverage assignments and whether forecast accuracy is a significant determinant. I seek to examine whether brokerage houses reward accurate financial analysts by assigning them to high-profile firms, thus providing analysts with incentives to issue accurate forecasts.

3. Data, measures, and descriptive statistics

3.1. *Data and descriptive statistics*

Data were obtained from the Institutional Brokers Estimate System (I/B/E/S) database. I use the earnings forecasts of analysts and the corresponding actual earnings for the 1981–2014 period. I also use information on analysts' stock recommendations. I/B/E/S recommendation data cover a shorter time period (1994–2014). Data on stock returns, market capitalisation and trading volume were obtained from the Center for Research in Security Prices (CRSP). Following existing conventions, only firms whose fiscal years end in December were retained in order to avoid the problem of non-overlapping forecasting horizons (Easterwood and Nutt 1999; Hong et al. 2000; Hong and Kubik 2003). The final sample covers the 1994–2014 period. It contains approximately 1.8 million earnings forecasts issued by 6,907 analysts on 9,466 firms. The total number of recommendations is 216,238.

Table 1 provides data on analyst characteristics and reports the annual descriptive statistics. The number of active analysts (firms) varies across years and ranges from 1,677 (2,483) to 2,780 (3,356). The numbers of firms and analysts tend to increase over time, reflecting the increased coverage of I/B/E/S. As a consequence, the total number of earnings forecasts increases from 45,697 in the first year of the sample to 113,195 in the last year. The average market capitalisation of the covered firms is about $9 billion. Finally, the average number of analysts issuing earnings forecasts for a firm is approximately 10. This is also the average number of firms each analyst covers.

3.2. *Measures of forecast accuracy, coverage assignments, and control variables*

3.2.1. *Quality of coverage assignments*

Two characteristics are considered in order to measure the quality of coverage assignments (i.e. whether an analyst covers high-profile firms): (1) stock market capitalisation and (2) trading volume.[6] For each industry and each year, firms are sorted according to their market capitalisation (alternatively, according to their trading volume).[7] I then assign a ranking based on this sorting; the largest firm (highest trading volume firm) receives the first rank, the second largest firm (second highest trading volume firm) receives the second rank, and so forth until the firm with the smallest capitalisation (lowest trading volume) receives the last rank. Because the number

Table 1. Descriptive statistics.

Year (1)	Number of analysts (2)	Number of earnings forecasts (3)	Number of analyst-firm-year observations (4)	Number of recommendations (5)	Number of firms (6)	Average market capitalisation (in $ billions) (7)	Number of analysts per firm (8)	Number of firms per analyst (9)
1994	1,677	45,697	15,532	8,011	2,483	4.03	9.16	11.13
1995	1,810	51,010	16,929	8,807	2,672	4.59	9.08	10.81
1996	2,009	55,077	18,770	9,288	3,192	4.82	8.46	10.72
1997	2,214	57,975	19,862	9,783	3,356	6.09	8.48	10.13
1998	2,400	66,505	20,426	11,502	3,290	7.37	8.50	9.65
1999	2,591	63,992	21,196	12,078	3,166	9.30	9.02	9.35
2000	2,701	62,274	20,741	11,341	3,007	1.12	9.25	8.96
2001	2,744	69,402	19,651	9,860	2,660	9.80	9.70	8.57
2002	2,588	67,044	19,368	14,547	2,631	8.29	9.71	8.75
2003	2,532	70,851	19,536	10,293	2,591	8.47	9.97	8.86
2004	2,657	81,810	21,858	10,051	2,802	9.14	10.02	9.11
2005	2,714	87,284	22,972	9,336	2,921	9.24	9.89	9.31
2006	2,777	92,838	24,451	10,063	3,008	9.41	9.93	9.54
2007	2,754	96,122	25,126	10,595	3,090	10.35	9.87	9.88
2008	2,663	107,252	24,296	11,785	2,936	8.62	9.92	9.92
2009	2,526	103,545	23,654	10,643	2,784	7.58	10.32	10.15
2010	2,703	109,187	25,666	10,286	2,792	9.43	11.15	10.27
2011	2,780	116,980	27,192	11,189	2,826	1.08	11.53	10.44
2012	2,655	121,048	27,602	9,981	2,856	11.32	11.51	10.90
2013	2,460	117,446	27,580	8,504	2,911	13.64	11.17	11.69
2014	2,225	113,195	26,736	8,295	3,100	15.59	10.13	12.54

Notes: This table reports year-by-year descriptive statistics. Column 2 displays the number of active analysts. Column 3 gives the total number of earnings forecasts. Column 4 provides the number of analyst-firm-year observations. Column 5 gives the number of recommendations issued by analysts. Column 6 displays the total number of firms. Column 7 provides the average market capitalisation of the firms covered by financial analysts. Finally, columns 8 and 9 report the number of analysts per firm and the number of firms per analyst, respectively.

of firms in each industry varies, firm rank is scaled by the number of firms belonging to each industry. The market capitalisation (trading volume) score is computed as follows:

$$SCORE_{j,t} = 100 - \left[\frac{RANK_{j,k,t} - 1}{N_{k,t} - 1}\right] \times 100, \tag{1}$$

where $N_{k,t}$ is the number of firms that belong to industry k in year t and $RANK_{j,k,t}$ is the capitalisation (trading volume) rank of firm j for year t.

This transformation of characteristics into scores facilitates comparison across industries: the largest firm (the firm with the highest trading volume) in industry A has the same value as the largest firm (the firm with the highest trading volume) in industry B. For a given industry and a given year, the firm with the largest market capitalisation (trading volume) receives a score of 100, while the firm with the smallest capitalisation (lowest trading volume) receives a score of 0. The use of scores, rather than absolute levels, also ensures that the results are not driven by an increase in average capitalisation (trading volume) over time.

The *exposure to large firms* of an analyst, for a given year, is defined as the average of the capitalisation scores of the firms he/she covers during that year. Similarly, the *exposure to trading volume* of an analyst for a given year is defined as the average of the trading volume scores of the firms he/she covers during that year.

3.2.2. *Internal career outcomes*

The study examines changes in the coverage assignments of financial analysts. To determine whether an analyst moves on to cover higher-profile firms, I look at whether an analyst increases (or decreases) his *exposure to large firms* (respectively, his/her *exposure to trading volume*) from one year to the next. My measures of internal career outcomes are defined as follows. For each year, analysts are ranked according to their *exposure to large firms* (*exposure to trading volume*). They are then assigned to 10 deciles. My measure of *Internal Promotion* takes a value of 1 if the analyst moves from decile q to decile q+1 between year t and year t+1. The measure takes a value of 0 if the previous condition is not met or if the analyst is laid off in year t+1. My measure of *Internal Demotion* takes a value of 1 if the analyst moves from decile q to decile $q-1$ of *exposure to large firms* (*exposure to trading volume*) between year t and year t+1 or if he/she is laid off in year t+1.

3.2.3. *Measures of forecast accuracy*

I use three different measures of forecast accuracy. To mitigate the issue of forecast horizon, I compute these three measures for each firm j and each year t based on the last forecast issued before a cut-off date of June 30. The first measure is the absolute forecast error (AFE). I compute AFE as follows:

$$AFE_{i,j,t} = \left|ACTUAL_{i,j,t} - FORECAST_{i,j,t}\right|, \tag{2}$$

where $AFE_{i,j,t}$ represents the absolute error of the forecast issued by analyst i on firm j in year t. I then measure the forecast performance for analyst i in year t by taking the average of the absolute forecast errors over all stocks the analyst follows in that year t.

The second measure of forecast accuracy is the measure of relative forecast accuracy of Hong et al. (2000). For each firm j and each year t, I order analysts based on their absolute forecast errors. The analyst with the lowest absolute forecast error receives the first rank, the analyst with the second lowest absolute forecast error receives the second rank, and so on. Analysts with the same *AFE* are assigned the same rank (the midpoint value of their ranks). The ranks are then transformed into scores in order to account for differences in the number of analysts covering the different firms. The scores are obtained by applying the following formula:

$$ACC\_SCORE_{i,j,t} = 100 - \left[\frac{ACC\_RANK_{i,j,t} - 1}{M_{j,t} - 1}\right] \times 100 \tag{3}$$

where $M_{j,t}$ is the number of analysts who follow firm *j* in year *t*, and $ACC\_RANK_{i,j,t}$ is the rank of analyst *i* based on the absolute forecast error of his/her forecast for firm *j* in year *t*. The forecast performance is then computed by taking the average of the accuracy scores (*ACC_SCORE*) over all firms covered by analyst *i* in year *t*.

The third measure of forecast accuracy is Clement's (1999) measure of relative forecast accuracy which compares an analyst's absolute forecast error to the average absolute forecast error of other analysts following the same firm. Formally, the accuracy of a forecast issued by analyst *i* on firm *j* in year *t* is defined by the proportional mean absolute forecast error (*PMAFE*), given by

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE}_{j,t}}{\overline{AFE}_{j,t}} \tag{4}$$

where $\overline{AFE}_{j,t}$ is the mean absolute forecast error of all analysts issuing earnings forecasts on firm *j* in year *t*. The forecast performance is then computed by taking the average of the proportional mean absolute forecast error (*PMAFE*) for all firms covered by analyst *i* in year *t*. To ensure that a meaningful comparison of forecast performance can be obtained across analysts, firms covered by fewer than 3 analysts and analysts covering fewer than 3 firms are removed from the sample (Hong and Kubik 2003).

3.2.4. *Measure of recommendation profitability*

Earnings forecasts are used by financial analysts as an input to their recommendations (Brown et al. 2015). Loh and Mian (2006) show that more proficient forecasters tend to issue more profitable recommendations; thus, it is necessary to control for recommendation profitability in order to show that forecast accuracy matters for internal career outcomes beyond the potential impact of recommendation profitability. I follow Loh and Mian (2006) and define the measure of recommendation profitability. For each analyst *i* in each year *t*, I build a portfolio of long and short positions based on outstanding recommendations. Stale recommendations, i.e. recommendations that are older than six months, are removed from the portfolio.[8] A firm is entered as a long position if the corresponding recommendation is a Buy or a Strong Buy. Short positions are determined by the Sell and Strong Sell recommendations. After determining the composition of each portfolio at the close of trading of day $\tau - 1$, I compute daily value-weighted returns for day τ. These daily returns are then compounded to obtain yearly returns (the portfolio is rebalanced every day). I then subtract the corresponding yearly market return. (I use the NYSE/AMEX/Nasdaq value-weighted index as a proxy for the market portfolio.) This simple market-adjusted return is retained as a measure of recommendation profitability.

3.2.5. *Measure of forecast boldness*

My measure of *Boldness* in the earnings forecasts is adapted from Hong et al. (2000). For firm *j* in year *t*, I define a measure of forecast consensus $\overline{F}_{j,t}$, as the average of the earnings forecasts made by all other analysts except analyst *i*. I then calculate the deviation from consensus as

$|F_{i,j,t} - \overline{F_{j,t}}|$. The process to obtain the *Boldness* measure is similar to the one used for the Hong et al. (2000) accuracy measure. For each firm and each year, I rank analysts according to their deviation from the consensus. These ranks are then transformed into scores as in Equation (3). The relative boldness measure, $Boldness_{i,t}$, is the average of the boldness scores over all the firms covered by analyst i in year t.

3.2.6. *Measure of forecast optimism*

My measure of *Optimism* in the earnings forecast is adapted from Hong and Kubik (2003). In each year t and for each firm j that analyst i follows, I create a dummy variable that takes a value of 1 if the analyst's forecast is greater than the consensus forecast (defined above) and 0 otherwise. I then retain the average of these dummy variables across the firms that the analyst covers each year. I then apply the same transformation as the one used for computing the *Boldness* measure. For each firm and each year, analysts are ranked according to the average of the dummy variables. I transform these ranks into scores as in Equation (3). The relative optimism measure, $Optimism_{i,t}$, is thus the average of the optimism scores over all firms covered by analyst i in year t.

3.2.7. *Other controls*

The measure of experience is built following Clement (1999). I define the *Experience* variable as the number of years for which the analyst has been submitting forecasts to the I/B/E/S database. Controls also include the logarithm of the number of firms covered and the number of industries covered. These two additional controls account for portfolio complexity.

4. Empirical results

4.1. *Forecast accuracy and internal career outcomes*

I examine the influence of past forecast accuracy on the type of firms covered by analysts with the following logit model specification:

$$\begin{aligned}&\Pr(\mathit{Internal\ promotion}_{i,t+1})\\ &= \operatorname{logit}\left(\begin{array}{c}\beta_0 + \beta_1 \mathit{Forecast\ accuracy\ indicator}_{i,t}\\ +\beta_2 \mathit{Recommendation\ profitability}_{i,t} + \beta_3 \mathit{Boldness}_{i,t} + \beta_4 \mathit{Optimism}_{i,t}\\ +\beta_5 \mathit{Experience}_{i,t} + \beta_6 \mathit{Log\ number\ of\ firms\ covered}_{i,t}\\ +\beta_7 \mathit{Number\ of\ industries\ covered}_{i,t} + \mathit{Year}_t\ \mathit{effects} + \epsilon_{i,t+1}\end{array}\right)\end{aligned} \quad (5)$$

where $\mathit{Internal\ promotion}_{i,t+1}$ is an analyst's favourable career outcome (i.e. whether analyst i moves from decile q of *exposure to large firms* (*exposure to trading volume*) in year t to decile q+1 in year t+1), and $\mathit{Forecast\ accuracy\ indicator}_{i,t}$ is a dummy variable that takes a value of 1 if analyst i is in the first (respectively, last) decile of forecast accuracy and 0 otherwise. $\mathit{Recommendation\ profitability}_{i,t}$ is the market-adjusted return of a portfolio based on the stock recommendations of analyst i in year t. I control for analysts' characteristics by adding the following control variables: *Boldness*, *Optimism*, *Experience*, *Log number of firms covered*, and *Number of industries covered*. Finally, a full set of year dummies (Year_t *effects*) is added.[9]

I am also interested in analysts' unfavourable career outcomes. I consider this second logit model specification:

$$\Pr(\textit{Internal demotion}_{i,t+1}) = \text{logit}\begin{pmatrix} \beta_0 + \beta_1 \textit{Forecast accuracy indicator}_{i,t} \\ +\beta_2 \textit{Recommendation profitability}_{i,t} + \beta_3 \textit{Boldness}_{i,t} + \beta_4 \textit{Optimism}_{i,t} \\ +\beta_5 \textit{Experience}_{i,t} + \beta_6 \textit{Log number of firms covered}_{i,t} \\ +\beta_7 \textit{Number of industries covered}_{i,t} + \textit{Year}_t \textit{ effects} + \epsilon_{i,t+1} \end{pmatrix} \quad (6)$$

where $\textit{Internal demotion}_{i,t+1}$ is an analyst's unfavourable career outcome (i.e. whether analyst i moves from decile q of *exposure to large firms* (*exposure to trading volume*) in year t to decile $q-1$ in year t+1 or analyst i is laid off in year t+1).

Table 2 presents the results of the estimation of these two logit models. In columns (1)–(6), the dependent variable is whether an analyst experiences an internal promotion, that is, whether an analyst moves to a higher decile of *exposure to large firms* in year t+1. The unconditional probability of experiencing an internal promotion is 33.42%.

Columns (1) and (2) show the effect of being in the bottom or top 10% of absolute forecast accuracy. In column (1), being in the bottom 10% of absolute forecast accuracy decreases the probability of experiencing a favourable career outcome (i.e. an internal promotion) by 3.50 percentage points. This effect is statistically significant at the one percent significance level. Given that in any year, 33.42% of analysts obtain an internal promotion, being in the bottom decile of accuracy decreases the likelihood of experiencing an internal promotion by about 10.5%. In contrast, being in the top decile of absolute forecast accuracy increases the likelihood of internal promotion by about 9.8%. Columns (3) and (4) report the results obtained using the relative measure of accuracy of Hong et al. (2000). Being in the bottom 10% of relative accuracy decreases the probability of experiencing an internal promotion by 3.58 percentage points. This effect is significant at the one percent significance level. Being among the worst forecasters therefore decreases an analyst's chances of experiencing a favourable internal career outcome by about 10.7%. With this measure of relative forecast accuracy, the impact of belonging to the most accurate forecasters (top decile of relative forecast accuracy) is not statistically significant. In columns (5) and (6), the measure of forecast accuracy that is used is Clement's (1999) measure of relative forecast accuracy. Being in the bottom (top) decile of relative forecast accuracy decreases (increases) the probability of moving to a higher decile of exposure to large firms by 2.41 (4.32) percentage points. These marginal probabilities indicate a 7.21% decrease in the likelihood of experiencing a favourable internal career outcome for the lowest decile and a 12.93% increase for the highest decile.

Columns (7)–(12) describe unfavourable career outcomes. The dependent variable here is whether an analyst experiences an internal demotion, that is, whether the analyst moves to a lower decile of *exposure to large firms* in year t+1 or is laid off in year t+1. Being in the bottom (top) decile of accuracy has a positive (negative) and statistically significant impact on the probability of experiencing an internal demotion. This result is consistent across the three different measures of accuracy. The largest effect for being in the bottom decile of accuracy is observed when Clement's (1999) relative measure is used: the chances for an analyst to be demoted increase by around 20% (an increase of 7.11 percentage points relative to an unconditional probability of demotion of 35.72%). I obtain these results while controlling for factors likely to impact coverage assignments such as recommendation profitability, forecast boldness, forecast optimism, analyst experience, and portfolio complexity (proxied by the log number of firms covered and the number of industries covered).

Table 2. Forecast accuracy and Exposure to large firms (ELF).

	Internal Promotion (*Exposure to large firms*)						Internal Demotion (*Exposure to large firms*)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bottom 10% of AFE	−0.1612***						0.1309***					
	(0.0404)						(0.0390)					
	[−0.0350]						[0.0303]					
Top 10% of AFE		0.1445***						−0.1831***				
		(0.0395)						(0.0400)				
		[0.0327]						[−0.0409]				
Bottom 10% of relative forecast accuracy (Hong et al. 2000)			−0.1653***						0.2423***			
			(0.0419)						(0.0393)			
			[−0.0358]						[0.0568]			
Top 10% of relative forecast accuracy (Hong et al. 2000)				0.0202						−0.0786**		
				(0.0403)						(0.0399)		
				[0.0045]						[−0.0178]		
Bottom 10% of relative forecast accuracy (Clement 1999)					−0.1103***						0.3017***	
					(0.0414)						(0.0392)	
					[−0.0241]						[0.0711]	
Top 10% of relative forecast accuracy (Clement 1999)						0.1902***						−0.1540***
						(0.0391)						(0.0397)
						[0.0432]						[−0.0345]
Recommendation profitability	0.0629***	0.0645***	0.0647***	0.0653***	0.0651***	0.0668***	−0.1843***	−0.1852***	−0.1853***	−0.1869***	−0.1857***	−0.1882***
	(0.0201)	(0.0200)	(0.0200)	(0.0200)	(0.0200)	(0.0200)	(0.0231)	(0.0231)	(0.0231)	(0.0231)	(0.0231)	(0.0231)
Forecast boldness	0.0009	0.0009	0.0008	0.0009	0.0011	0.0007	−0.0013*	−0.0014*	−0.0012	−0.0011	−0.0019**	−0.0012
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Forecast optimism	0.1204**	0.1209**	0.1321***	0.1316***	0.1284***	0.1310***	0.1597***	0.1639***	0.1488***	0.1491***	0.1586***	0.1505***
	(0.0480)	(0.0481)	(0.0480)	(0.0480)	(0.0480)	(0.0479)	(0.0473)	(0.0473)	(0.0472)	(0.0472)	(0.0472)	(0.0472)
Experience	0.0014	0.0017	0.0017	0.0018	0.0017	0.0018	−0.0045**	−0.0047**	−0.0048**	−0.0048**	−0.0046**	−0.0049**
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Log number of firms covered	0.2433***	0.2607***	0.2213***	0.2458***	0.2321***	0.2652***	−0.5927***	−0.6150***	−0.5596***	−0.6025***	−0.5610***	−0.6109***
	(0.0609)	(0.0612)	(0.0613)	(0.0612)	(0.0612)	(0.0612)	(0.0604)	(0.0605)	(0.0606)	(0.0605)	(0.0605)	(0.0605)

(*Continued*)

Table 2. Continued.

	Internal Promotion (*Exposure to large firms*)						Internal Demotion (*Exposure to large firms*)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Number of industries covered	−0.0184***	−0.0196***	−0.0183***	−0.0193***	−0.0187***	−0.0199***	0.0123**	0.0136**	0.0116*	0.0133**	0.0115*	0.0136**
	(0.0059)	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0061)
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619
Log likelihood	−20,589.10	−20,590.54	−20,589.27	−20,597.05	−20,593.58	−20,585.48	−20,752.54	−20,747.51	−20,739.33	−20,756.18	−20,728.83	−20,750.53

Notes: Financial analysts are tracked to examine whether past forecast accuracy affects the likelihood that they see their *exposure to large firms* (*ELF*) increase or decrease. I consider that an analyst experiences an internal promotion in year t+1 if he/she moves from decile q of *exposure to large firms* to decile q+1 between year t and year t +1. I consider that an analyst experiences an internal demotion in year t+1 if he/she moves from decile q of *exposure to large firms* to decile q−1 between year t and year t +1 or if he/she is laid off in year t+1. The logit specifications are in Equations (5) and (6). I report logit coefficients; standard errors are in parentheses. The entries in brackets are the marginal probabilities that an analyst will have an internal promotion (or demotion) compared with other analysts. ***/**/* correspond to 1%/5%/10% significance levels, respectively.

Table 3 reports similar results. However, the quality of coverage assignments in this table is defined with respect to the trading volume of covered firms. In columns (1)–(6), the dependent variable is whether an analyst moves to a higher decile of *exposure to trading volume* in year $t+1$. In columns (7)–(12), the dependent variable is whether an analyst experiences an internal demotion, that is, whether the analyst moves to a lower decile of *exposure to trading volume* in year $t+1$ or is laid off in year $t+1$. The findings are unchanged when the quality of coverage assignments is assessed with the trading volume rather than with the market capitalisation.

Despite having controlled for analysts' experience in the previous test, it is important to verify that the relationship between forecast accuracy and coverage assignments is not a by-product of analyst experience. Clement (1999) finds that experienced analysts tend to be more accurate than their inexperienced peers. My results could therefore reflect the fact that the speed of evolution towards large stocks is higher for experienced analysts who tend to be more accurate than their peers. To demonstrate that the relationship between accuracy and coverage assignments is not spurious, I estimate the previous regressions on a subsample of experienced financial analysts (i.e. with more than 5 years of experience). The results presented in Table 4 are similar to the ones in Tables 2 and 3. This additional test indicates that the relationship between forecast accuracy and coverage assignments is not a by-product of analysts' experience.

Overall, these results show that accurate forecasters move on to higher-profile firms, while the quality of coverage assignments decreases for analysts issuing inaccurate forecasts. These empirical findings reveal the existence of a relationship between forecast accuracy and the quality of coverage assignments. However, further analysis is needed to show that brokerage houses assign higher-profile firms to accurate forecasters. Indeed, there is a possibility that these results may be driven by a survivorship bias: accurate forecasters manage to remain in the profession (i.e. they do not get laid off) and gradually manage to cover high-profile firms. Additionally, by construction, it is possible that an analyst appears to experience an internal promotion (or demotion) while the portfolio of firms he/she covers remains the same. This situation is likely to occur if the capitalisation (alternatively, the trading volume) of the covered stocks increase or decrease greatly from one year to the next. Given these different elements, an additional analysis is needed to confirm the link between forecast accuracy and the coverage of high-profile firms. In the following subsection, I investigate whether accurate analysts are more likely to be selected when their brokerage house initiates the coverage of a high-profile firm.

4.2. *Forecast accuracy and coverage initiation*

In this test, I examine coverage initiation by brokerage houses to determine whether brokerage houses tend to favour accurate analysts when they initiate coverage of high-profile firms. Being assigned the coverage of a high-profile firm is a favourable outcome since the rewards (investor recognition, potential commissions, etc.) of covering such a firm are much greater than those of covering a small firm. This analysis looks directly at the competition within brokerage houses.

My sample of coverage initiation consists of all the firms that are covered in year t, but not in year $t-1$, by brokerage house k. Analysts tend to specialise by industry (Sonney 2009; Kadan et al. 2012). The sample of coverage initiation is therefore restricted to firms belonging to the main industry of analyst i, who initiates the coverage. As the main interest here is that of internal career outcomes, I also exclude initiations made by analysts who were not employed by the same brokerage house in year $t-1$. I then look at the other analysts, employed by the brokerage house in year $t-1$, who could have potentially been selected for the coverage initiation. I require that these analysts are still employed by the brokerage house at time t and that their main industry at time $t-1$ corresponds to the industry to which the new covered firm belongs. Finally, for a coverage

Table 3. Forecast accuracy and Exposure to trading volume (ETV).

	Internal Promotion (*Exposure to trading volume*)						Internal Demotion (*Exposure to trading volume*)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bottom 10% of AFE	−0.1524***						0.1907***					
	(0.0401)						(0.0385)					
	[−0.0334]						[0.0450]					
Top 10% of AFE		0.1765***						−0.1745***				
		(0.0392)						(0.0396)				
		[0.0404]						[−0.0396]				
Bottom 10% of relative forecast accuracy (Hong et al. 2000)			−0.1498***						0.2339***			
			(0.0416)						(0.0391)			
			[−0.0329]						[0.0554]			
Top 10% of relative forecast accuracy (Hong et al. 2000)				−0.0011						−0.0303		
				(0.0402)						(0.0393)		
				[−0.0003]						[−0.0070]		
Bottom 10% of relative forecast accuracy (Clement 1999)					−0.1392***						0.3154***	
					(0.0413)						(0.0389)	
					[−0.0306]						[0.0752]	
Top 10% of relative forecast accuracy (Clement 1999)						0.1818***						−0.0928**
						(0.0389)						(0.0391)
						[0.0416]						[−0.0213]
Recommendation profitability	0.0794***	0.0806***	0.0810***	0.0816***	0.0813***	0.0831***	−0.1200***	−0.1221***	−0.1222***	−0.1235***	−0.1225***	−0.1243***
	(0.0200)	(0.0200)	(0.0200)	(0.0200)	(0.0200)	(0.0200)	(0.0216)	(0.0217)	(0.0217)	(0.0217)	(0.0216)	(0.0217)
Forecast boldness	0.0009	0.0009	0.0008	0.0009	0.0011	0.0006	−0.0007	−0.0007	−0.0006	−0.0006	−0.0013	−0.0006
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Forecast optimism	0.1733***	0.1709***	0.1844***	0.1836***	0.1800***	0.1833***	0.0477	0.0470	0.0328	0.0337	0.0427	0.0342
	(0.0478)	(0.0478)	(0.0478)	(0.0477)	(0.0478)	(0.0477)	(0.0469)	(0.0469)	(0.0468)	(0.0468)	(0.0468)	(0.0468)
Experience	0.0031	0.0034	0.0034	0.0035	0.0034	0.0035	−0.0036*	−0.0039*	−0.0040*	−0.0041*	−0.0038*	−0.0041*
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Log number of firms covered	0.2377***	0.2590***	0.2176***	0.2377***	0.2234***	0.2585***	−0.5100***	−0.5321***	−0.4790***	−0.5150***	−0.4779***	−0.5220***
	(0.0603)	(0.0605)	(0.0606)	(0.0605)	(0.0605)	(0.0606)	(0.0615)	(0.0615)	(0.0615)	(0.0615)	(0.0614)	(0.0614)
Number of industries covered	−0.0164***	−0.0176***	−0.0162***	−0.0171***	−0.0164***	−0.0177***	0.0013	0.0030	0.0011	0.0026	0.0009	0.0028
	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0063)	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0062)

Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619	32,619
Log-likelihood	−20,758.15	−20,755.44	−20,758.89	−20,765.47	−20,759.72	−20,754.70	−21,007.47	−21,009.78	−21,001.86	−21,019.31	−20,987.12	−21,016.77

Notes: Financial analysts are tracked to examine if past forecast accuracy affects the likelihood that they see their *exposure to trading volume* (*ETV*) increase or decrease. I consider that an analyst experiences an internal promotion in year t+1 if he/she moves from decile q of *exposure to trading volume* to decile q+1 between year t and year $t+1$. I consider that an analyst experiences an internal demotion in year t+1 if he/she moves from decile q of *exposure to trading volume* to decile $q-1$ between year t and year $t+1$ or if he/she is laid off in year t+1. The logit specifications are in Equations (5) and (6). I report logit coefficients; standard errors are in parentheses. The entries in brackets are the marginal probabilities that an analyst will have an internal promotion (or demotion) compared with other analysts. ***/**/* correspond to 1%/5%/10% significance levels, respectively.

Table 4. Influence of experience on the relationship between forecast accuracy and coverage assignments.

	Panel A: Forecast accuracy and Exposure to large firms											
	Internal Promotion (Exposure to large firms)						Internal Demotion (*Exposure to large firms*)					
Bottom 10% of AFE	−0.1980*** (0.0520) [−0.0430]						0.1883*** (0.0504) [0.0430]					
Top 10% of AFE		0.1122** (0.0509) [0.0254]						−0.1419*** (0.0519) [−0.0311]				
Bottom 10% of relative forecast accuracy (Hong et al. 2000)			−0.1591*** (0.0545) [−0.0348]						0.2482*** (0.0518) [0.0571]			
Top 10% of relative forecast accuracy (Hong et al. 2000)				0.0240 (0.0527) [0.0054]						−0.0416 (0.0529) [−0.0092]		
Bottom 10% of relative forecast accuracy (Clement 1999)					−0.1358** (0.0538) [−0.0298]						0.3307*** (0.0513) [0.0767]	
Top 10% of relative forecast accuracy (Clement 1999)						0.2198*** (0.0508) [0.0505]						−0.1435*** (0.0525) [−0.0314]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833
Log likelihood	−13,201.35	−13,206.33	−13,204.42	−13,208.63	−13,205.50	−13,199.48	−13,030.49	−13,033.59	−13,026.05	−13,037.06	−13,016.92	−13,033.60

Panel B: Forecast accuracy and Exposure to trading volume

	Internal Promotion (*Exposure to trading volume*)						Internal Demotion (*Exposure to trading volume*)					
Bottom 10% of AFE	−0.1934*** (0.0516) [−0.0426]						0.2349*** (0.0498) [0.0546]					
Top 10% of AFE		0.1224** (0.0506) [0.0281]						−0.1414*** (0.0514) [−0.0315]				
Bottom 10% of relative forecast accuracy (Hong et al. 2000)			−0.1989*** (0.0546) [−0.0438]						0.2741*** (0.0514) [0.0641]			
Top 10% of relative forecast accuracy (Hong et al. 2000)				−0.0509 (0.0529) [−0.0114]						0.0286 (0.0519) [0.0065]		
Bottom 10% of relative forecast accuracy (Clement 1999)					−0.1351** (0.0535) [−0.0300]						0.3583*** (0.0509) [0.0844]	
Top 10% of relative forecast accuracy (Clement 1999)						0.2084*** (0.0506) [0.0483]						−0.0770 (0.0516) [−0.0173]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833	20,833
Log likelihood	−13,321.19	−13,325.45	−13,321.58	−13,327.88	−13,325.12	−13,319.97	−13,214.61	−13,221.74	−13,211.51	−13,225.41	−13,201.10	−13,224.44

Notes: This table reproduces the analysis presented in Tables 2 and 3 on a subsample of financial analysts with more than 5 years of experience.

initiation to be included in the sample, I require that at least three other analysts could have initiated the coverage. (Otherwise, there is not enough competition within the brokerage house.) This analysis relates the probability that an analyst initiates the coverage of a given firm for the brokerage house to whether the analyst was the most accurate forecaster among the potential candidates to the initiation. I also relate the likelihood of initiating the coverage to the analyst's industry knowledge.[10] The regression specification is the following:

$$\begin{aligned}
&\Pr(\mathit{Coverage\ initiation}_{i,j,k,t}) \\
&= \operatorname{logit}\left(\begin{array}{c}
\beta_0 + \beta_1 \mathit{Top\ forecaster}_{i,j,k,t-1} + \beta_2 \mathit{Industry\ knowledge\ dummy}_{i,j,k,t-1} \\
+\beta_3 \mathit{Recommendation\ profitability}_{i,t-1} + \beta_4 \mathit{Boldness}_{i,t-1} \\
+\beta_5 \mathit{Optimism}_{i,t-1} + \beta_6 \mathit{Prestige\ of\ existing\ coverage}_{i,t-1} \\
+\beta_7 \mathit{Experience}_{i,t-1} + \beta_8 \mathit{Log\ number\ of\ firms\ covered}_{i,t-1} \\
+\beta_9 \mathit{Number\ of\ industries\ covered}_{i,t-1} + \epsilon_{i,j,k,t}
\end{array}\right)
\end{aligned} \tag{7}$$

where $\mathit{Coverage\ initiation}_{i,j,t}$ is a dummy variable that takes a value of 1 if analyst i is assigned to the coverage initiation of firm j by brokerage house k in year t; otherwise, it takes a value of 0. $\mathit{Top\ forecaster}_{i,j,k,t-1}$ is a dummy variable that takes a value of 1 if analyst i is the most accurate analyst[11] compared with other analysts employed by brokerage house k who were potential candidates for the coverage initiation of firm j by brokerage house k; otherwise, it takes a value of 0. $\mathit{Industry\ knowledge\ dummy}_{i,j,k,t-1}$ is a dummy variable that takes a value of 1 if analyst i covers the highest number of firms in the industry of firm j, in year $t-1$, compared with other analysts in brokerage house k who were potential candidates for the coverage initiation of firm j; otherwise, it takes a value of 0. $\mathit{Prestige\ of\ existing\ coverage}_{i,t-1}$ is measured by taking the average capitalisation of the stocks covered in year $t-1$ by analyst i. Other controls are defined in the same way as in the previous regressions. The coefficient of interest is β_1.

I am interested in estimating the regression in Equation (7) for the subsample of high-profile firms. I classify a firm as high-profile if it is one of the five largest firms (or alternatively, is among the five firms with the highest trading volume) in its industry. About 3% of coverage initiations are classified as high-profile. I first estimate the regression using all initiations as a benchmark. I then estimate the regression using only high-profile firms. Of interest is the difference in magnitudes between β_1 for the subsample of high-profile firms and the sample comprising all firms.

The results are reported in Table 5. Column (1) displays the benchmark case (all initiations). Consistent with previous literature and with the survey findings of Brown et al. (2015), industry knowledge is the main predictor of coverage initiation. The analyst who covers the most firms in an industry is the most likely candidate to be selected by the brokerage house to initiate the coverage of a firm in that industry. The most accurate analyst at a brokerage house is not more likely to initiate coverage than any other analyst; β_1 is not significantly different from zero. Columns (2) and (3) present the regression results for the coverage initiation of high-profile firms. The coefficient for *Top forecaster* is positive and highly significant. Being the most accurate analyst increases the likelihood of initiating coverage by about 7 percentage points. For high-profile firms, where coverage choices are likely to be constrained by brokerage houses, forecast accuracy is an important determinant for an analyst to initiate coverage. Industry knowledge is no longer significant when only high-profile firms are considered. Overall, these results confirm my previous findings and suggest that forecast accuracy matters for covering high-profile firms.

Table 5. The effect of accuracy on whether an analyst is assigned to initiate the coverage of a firm by his/her brokerage house.

	Coverage initiation		
	All firms	Large capitalisation firms	High trading volume firms
	(1)	(2)	(3)
Top forecaster	0.0213	0.4899***	0.4342***
	(0.0421)	(0.2402)	(0.2209)
	[0.0033]	[0.0749]	[0.0691]
Industry knowledge dummy	0.3376***	−0.0915	−0.3683
	(0.0421)	(0.2646)	(0.2564)
	[0.0548]	[−0.0125]	[−0.0509]
Controls			
Recommendation profitability	Yes	Yes	Yes
Prestige of existing coverage	Yes	Yes	Yes
Forecast boldness	Yes	Yes	Yes
Forecast optimism	Yes	Yes	Yes
Experience	Yes	Yes	Yes
Log number of firms covered	Yes	Yes	Yes
Numbers of industries covered	Yes	Yes	Yes
Number of observations	23,570	646	741
Log-likelihood	−11,424.72	−289.83	−342.54

Notes: Financial analysts are tracked to examine whether past forecast accuracy affects the likelihood that they will initiate coverage of a high-profile firm for their brokerage house. Clement's (1999) measure of relative forecast accuracy is used to build the *Top forecaster variable*. The sample of coverage initiation consists of all the firms that are covered by brokerage house k in year t but not in year $t-1$. Potential candidates for the coverage initiation of firm j in year t are analysts whose main industry in year $t-1$ corresponds to the industry of firm j. A minimum of four competing analysts is necessary for the coverage initiation to be included in the sample. The regression specification is in Equation (7). In column (1), the sample contains all initiations. In columns (2) and (3), the sample contains only coverage initiations of high-profile firms. I report logit coefficients; standard errors are in parentheses. The entries in brackets are the marginal probabilities that an analyst will initiate coverage compared with other analysts. ***/**/* correspond to 1%/5%/10% significance levels, respectively.

5. Conclusion

This article provides evidence that brokerage houses reward their most accurate analysts by assigning them to high-profile firms. Covering high-profile firms has a direct impact on the future compensation of analysts because it increases recognition, brings substantial media attention and implies greater potential investment banking and trading commissions (Jackson 2005; Groysberg et al. 2011). Overall, these findings indicate that issuing accurate earnings forecasts can lead to increased future compensation, and as such are a valuable contribution to the literature on the relationship between forecast accuracy and career outcomes.

I interpret my findings on forecast accuracy as a result of brokerage houses' concerns for reputation. The structure of analysts' compensation provides them with incentives to generate biased forecasts. However, biased forecasts can potentially hurt the reputation of the brokerage house and, consequently reduce the potential for future revenues. For instance, analysts who issue biased forecasts (optimistic forecasts) generate more trading commissions for their brokerage firms. However, this behaviour comes at the cost of reputation and decreases the long-term gains from building a good reputation. My results support the idea that brokerage houses provide analysts with short-term incentives (compensation structure) to maximise revenues from investment banking and trading commissions, and with long-term incentives (constraints on coverage decisions) to maximise their reputation and guarantee future revenue streams. My findings contribute to the literature on conflicts of interest. I document that conflicts of interest may be mitigated by brokerage houses providing analysts with incentives to issue accurate forecasts.

Notes

1. The analysts surveyed in Brown et al. (2015) rate broker votes and analyst rankings as the second most important determinant of their compensation.
2. Changes in regulations such as Reg FD and the Global Settlement impose that analyst compensation cannot be based directly or indirectly upon investment banking revenues. However, in practice, conflicts of interest remain prevalent, and analyst incentives are still linked with investment banking concerns. In their recent survey of sell-side analysts, Brown et al. (2015, p. 4) report that

   > In spite of [the SEC and the major U.S. exchanges'] efforts, 44% of our respondents say their success in generating underwriting business or trading commissions is very important to their compensation, suggesting conflicts of interest remain a persistent concerns for users of sell-side research.

3. However, because these two characteristics are correlated, my results are likely to remain unchanged when I focus on trading volume rather than market capitalisation.
4. Industry knowledge is measured by examining at whether the analyst covers the most stocks of the industry under consideration in his/her brokerage house.
5. Groysberg et al. (2011), using proprietary data on analyst compensation, find no evidence of a direct impact of forecast accuracy on compensation. Brown et al. (2015), however, report that 35% of the analysts they surveyed indicated that earnings forecast accuracy is a very important determinant of their compensation.
6. I make the implicit assumption that brokerage houses share similar preferences. Of course, it is possible that in some specialized brokerage houses, the competition is not for the coverage of large capitalisation/high trading volume but for firms with different characteristics.
7. I define industries using the Fama–French 48-industry classification (Fama and French 1997).
8. Womack (1996) finds that analyst recommendations retain investment value for up to six months.
9. Table A1, in the appendix, provides the correlation coefficients of the regression variables.
10. Brown et al. (2015) find that industry knowledge is very important to sell-side analysts: it is the most useful input for their earnings forecasts and stock recommendations, and it is an important determinant of analyst compensation. In addition, *Institutional Investor* (*II*) surveys regularly find that industry knowledge is extremely valuable to buy-side clients (Bagnoli et al. 2008).

11. I use Clement's (1999) measure of relative forecast accuracy to assess which analyst is the most accurate.

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Appendix

Table A1. Correlation coefficients of the regression variables.

	AFE	Measure of Hong et al. (2000)	Measure of Clement (1999)	Exposure to large firms	Exposure to trading volume	Recommendation profitability	Forecast boldness	Forecast optimism	Experience	Log number of firms covered
Panel A: Pearson's correlation coefficient										
Measure of Hong et al. (2000)	−0.06%									
Measure of Clement (1999)	0.19%	**−75.67%**								
Exposure to large firms	**−1.61%**	**−1.32%**	**1.58%**							
Exposure to trading volume	**−0.94%**	**−1.43%**	**1.58%**	**94.11%**						
Recommendation profitability	−0.02%	0.76%	−0.15%	**−4.92%**	**−3.10%**					
Forecast boldness	−0.10%	**16.25%**	**3.71%**	**2.31%**	**2.22%**	**1.31%**				
Forecast optimism	**−2.25%**	**−3.09%**	−0.79%	**8.14%**	**8.30%**	**5.08%**	**−2.32%**			
Experience	−0.56%	0.72%	**−1.87%**	**10.87%**	**7.58%**	**−1.44%**	**2.33%**	**2.20%**		
Log number of firms covered	**3.19%**	0.63%	**−2.20%**	**−3.84%**	**−6.56%**	**2.56%**	1.15%	**−1.69%**	**24.04%**	
Number of industries covered	**3.26%**	−0.66%	−0.30%	**−2.77%**	**−5.53%**	**1.79%**	0.20%	**−1.59%**	**19.90%**	**91.07%**
Panel B: Spearman's correlation coefficient										
Measure of Hong et al. (2000)	**−16.71%**									
Measure of Clement (1999)	**20.61%**	**−81.97%**								
Exposure to large firms	**−9.27%**	**−1.11%**	**−1.40%**							
Exposure to trading volume	**−3.92%**	**−1.28%**	**−1.23%**	**93.64%**						
Recommendation profitability	**−4.30%**	**1.37%**	−0.71%	**−4.02%**	**−4.26%**					
Forecast boldness	**−0.94%**	**15.78%**	**−1.22%**	**2.35%**	**2.28%**	**1.80%**				
Forecast optimism	**−9.67%**	**−2.28%**	−0.39%	**7.84%**	**7.96%**	**7.68%**	**−1.97%**			
Experience	0.20%	0.67%	−0.42%	**10.72%**	**6.98%**	**1.20%**	**2.69%**	**1.49%**		
Log number of firms covered	**18.06%**	0.08%	**2.53%**	**−5.27%**	**−7.98%**	**6.66%**	**0.95%**	**−2.05%**	**27.41%**	
Number of industries covered	**18.08%**	0.08%	**2.53%**	**−5.21%**	**−7.89%**	**6.66%**	**0.93%**	**−1.99%**	**27.38%**	**99.97%**

Notes: Panel A (Panel B) shows the Pearson (Spearman) correlation coefficients for the regression variables. Coefficients in bold are statistically significant at the 10% level.