Stock analysts affiliated with debt underwriters: are they different from their counterparts at equity underwriters?

Nguyen Manh Hiep[1]
ESCP Europe

Michael Troege[2]
ESCP Europe

Third draft, July 2018

Abstract: The paper compares earnings forecasts of analysts affiliated with debt underwriters to the forecasts of analysts affiliated with equity underwriters. We demonstrate that while analysts affiliated with equity underwriters produce more overly optimistic and inaccurate forecasts, analysts affiliated with debt underwriter affiliation often issue very precise, slightly pessimistic forecasts that can be marginally beaten by management. With increasing default risk, however, the behavior of debt-underwriter analysts increasingly resembles the behavior of equity-underwriter analysts. These results shed new light on the different conflicts of interest that influence analysts reporting behavior.

Keywords: affiliated analysts, earnings forecasts, financial distress, market reaction

JEL code: G14, G24, M41

---

[1] Nguyen Manh Hiep receives financing from The Ministry of Education and Training of Viet Nam and The Laboratory of Excellence for Financial Regulation (Labex Refi), an initiative lead by ESCP Europe, CNAM, ENA, and University Paris 1 Panthéon-Sorbonne (CES, PRISM and IRJS).
[2] Corresponding author, ESCP Europe, Paris Campus, 79, avenue de la République, 75543 Paris Cedex 11, France, Email : troege@escpeurope.eu.
The authors would like to thank Prof. Francois Derrien, HEC Paris, other participants at the 2018's AFFI conference, and the professors at ESCP Europe's Department of Finance for their valuable comments and suggestions.
----

1. Introduction

Financial analysts play an essential role in reducing information asymmetries and increasing market efficiency (Kelly and Ljungqvist, 2012, Derrien and Kecskés, 2013, Ellul and Panayides, 2018). The quality of their forecasts and recommendations is affected by a number of conflicts of interests, notably the underwriting relationship between their employers and the followed firms (Lin and McNichols, 1998, Michaely et al., 1999, Dechow et al., 2000, Bradshaw et al., 2001, James and Karceski, 2006, O'Brien et al., 2005, Degeorge et al., 2007). Existing studies have focused on equity underwriting relationship, and either disregarded debt underwriting relationship, or treated affiliation to debt underwriters and equity underwriters homogeneously, in effect overlooked their different nature. In this paper, we aim at a better understanding of stock analysts' conflicts of interests by investigating the behaviors of the stock analysts affiliated with debt underwriters and compare them to those of the stock analysts affiliated with equity underwriters and unaffiliated analysts.

The different nature between analysts affiliated with debt underwriters and equity underwriters lies in the implicit commitment to support the aftermarket of the security their employers underwrite. Underwriters are responsible for the sales, and buying all unsold amount of an offering. The success of an offering depends on the underwriter's reputation, business network and customer portfolio (Bajo et al., 2016). Post-offering performance of the securities has crucial consequences on both the returns of their portfolios, and their reputation to customers and business partners who have taken part in the issuance. These investors, who would not happy if an analyst downgrades a security they have taken a position in, are a group of actors potentially distorting analysts' incentives (Bradshaw, 2011). Underwriters implicitly commit to build market liquidity and support the underwritten securities post-offering. Therefore, after the offerings, analysts affiliated with equity underwriters are concerned with supporting stock price, whereas, analysts affiliated with debt underwriters are concerned with supporting debt price and relatively impartial about stock price. Given that favorable analysis reports create positive stock price reactions (Asquith et al., 2005), analysts affiliated with equity underwriters may be tempted to issue inaccurately overoptimistic reports to support the aftermarket stock performance, whereas, analysts affiliated with debt underwriters do not have the same incentive, because debt value and equity value are normally uncorrelated. We label this the "investor relationship hypothesis".

Over-optimism of analysts affiliated with equity underwriters has been widely recognized in extant literature (Lin and McNichols, 1998, Dechow et al., 2000, Bradshaw et al., 2001, Hong and Kubik, 2003, O'Brien et al., 2005, James and Karceski, 2006) as well as in our own empirical tests that follow. Over-optimism is generated by the analysts' under-reaction to negative information and over-reaction to positive information (Easterwood and Nutt, 1999), and fixation on accounting earnings without accounting for the low persistence of accruals (Bradshaw et al., 2001, Drake and Myers, 2011). Such irrationality seems to be more a consequence of strategic behavior rather than negligence (Raedy et al., 2006). The predominant view is that because (1) the firm management loves optimistic forecasts, and (2) underwriting relationship is costly to build and maintain, investment banks pressure their analysts to favor overly optimistic forecasts. We label this the "banking relationship hypothesis". If this hypothesis is true, analysts affiliated with debt underwriters must be as over-optimistic as analysts affiliated with equity underwriters, since they have the same motivation to cultivate banking relationship. However, we find that analysts affiliated with debt underwriters are significantly more accurate and less optimistic than both unaffiliated analysts and analysts affiliated with equity underwriters. This finding disproves the banking relationship hypothesis and supports the investor relationship hypothesis.

We are not the first who defies the banking relationship hypothesis. Understandably, managers dislike pessimistic opinions about their firms. In his book *Exile on Wall Street: One Analyst's Fight to Save the Big Banks from Themselves*, Mayo (2012) tells the story of how his conservative views of the firms invite hostile reactions from their managers. However, firm management does not necessarily fancy optimistic forecasts as the banking relationship hypothesis presumes. Bradshaw (2011) raises doubts over the assumption that overly optimistic coverage is intended to curry favor with the company, pointing out that optimistic forecasts, which are to be missed by actual earnings, can harm the managers' reputation and depress stock price (Graham et al., 2005). Ljungqvist et al. (2006) find no evidence that overoptimistic analysts help the banks attract underwriting mandates.

If the management of the firm likes neither pessimistic forecast nor optimistic forecasts, what do they like? Degeorge et al. (1999) assert that managers have strong incentives to "meet or beat" analysts' forecasts. Bartov et al. (2002) demonstrate that consistently reporting positive earnings surprises creates higher stock returns and stock valuations that cannot be explained by the firm's performance. This view is corroborated by numerous studies from the earnings management and forecast management literature (Matsumoto, 2002, Burgstahler and Eames, 2006, Roychowdhury, 2006, Beyer, 2008, Bernhardt and Campello, 2007, Quinn, 2018). According to this strand of study, if analysts want to court the firm management, they must cooperate and publish accurate or slightly pessimistic forecasts. This obviously and strikingly contrast with the banking relationship hypothesis. We label this the "earnings guidance hypothesis". Consistent with these studies, we observe that most forecasts are either accurate or slightly pessimistic. Intriguingly, we observe that analysts affiliated with debt underwriters are much more likely than other analysts to issue earnings forecasts that are just slightly below actual reported earnings. We also find that analysts are more likely to publish slightly pessimistic forecasts for larger firms. This phenomenon is particularly strong among analysts affiliated with equity underwriters.

By piecing together these different arguments with new empirical results, we fill the gap in these contradictory lines of existing literature. First, because the management of the followed firms prefer accurate or slightly pessimistic forecasts, and the investors in debt are indifferent about firm performance, analysts affiliated with debt underwriters cooperate with the firm managers and publish accurate or slightly pessimistic forecasts. Second, although analysts at equity underwriters can do the same, they are afflicted by the investor relationship concern, therefore diverted from cooperating with the firm management, and inclined towards producing overly optimistic forecasts to support aftermarket stock price. However, banking relationship is more important for larger firms, thus overrides the stock performance concern, and makes analysts affiliated with equity underwriters cooperate more closely with firm management. Third, because unaffiliated analysts do not enjoy access to inside information and communication with management, they are less able to coordinate their forecasts as precisely as affiliated analysts. These are the key findings of our paper.

So far, we argue that analysts affiliated with debt underwriters behave differently from their counterparts at equity underwriters because they are concerned with debt price and impartial about stock price and thus firm performance forecasts. Although debt and equity value are normally uncorrelated, their correlation gets higher with the level of financial distress risk. If our arguments are true, analysts at debt underwriters are increasingly partial about stock price and firm performance when financial distress risk increases. They can support debt price indirectly by supporting stock price. Accordingly, they deviate from cooperating with the firm management in favor of their investor relationship concern, and publish less accurate, more optimistic earnings forecasts. In other words, their behaviors converge to those of analysts affiliated with equity underwriters when financial distress risk is higher. Consistent with this conjecture, our empirical tests indicate that forecast errors and optimism of analysts affiliated with debt underwriters increase much faster than other analysts when financial distress risk increases.

Our results evidence that information flows from debt underwriting division to equity research division within an investment bank, helping stock analysts produce superior forecasts. Moreover, the finding that stock analysts at debt underwriters change their behavior to support debt price when the followed firms are in financial distress shows close cooperation between different departments of a financial institution towards a common goal. These results contribute to the strand of literature on information sharing within an investment bank or a financial conglomerate. Chen and Martin (2011) demonstrate that commercial banking relationship with the covered firms significantly improves analysts' accuracy, suggesting that information is shared between commercial banking division and equity research division. Hwang et al. (2018) show that after M&As, the acquirer-analysts' earnings forecasts for merged firms are substantially more accurate if they have in-house colleagues covering target firms prior to M&As. Other papers reveal that information is shared among different departments within a bank, such as between analysts and asset managers (Haushalter and Lowry, 2011), between economists and analysts, or between fund families and banks in the same financial conglomerate. Perhaps most related to our study, Hugon et al. (2016) suggest that equity analysts benefit from in-house debt research, particularly from cash-flow forecasts in debt research.

The rest of the paper is structured as follows: Section 2 develops hypotheses; Section 3 introduces the data, methodology and variable construction; Section 4 describes the data and presents selected results; Section 5 concludes.

2. Hypotheses

Figure 1 summarizes the types of forecasts and their respective uses. First, analysts affiliated with debt underwriters are not prone to the aftermarket stock performance concern as long as financial distress risk is moderate, and thus collide with the firms and make accurate or slightly pessimistic forecasts. Second, analysts affiliated with equity underwriters are afflicted by both stock performance concern and banking relationship concerned, hence should either makes optimistic or accurate and slightly pessimistic forecasts. Their choice between the two is therefore a practical question, but they must be more likely than other analysts to publish over-optimistic forecasts. Unaffiliated analysts try to be accurate or slightly pessimistic, but they are less likely to success than debt underwriters, because they do not enjoy as close a relationship with the followed firm.

[Figure 1 inserts here]

In accordance with the above mentioned studies and conjectures, we propose the following hypotheses.

H1: Forecasts by analysts affiliated with debt underwriters are more likely to be slightly pessimistic than other analysts.

H2: Forecasts by analysts affiliated with equity underwriters are more likely to be optimistic than other analysts.

H3: Analysts affiliated with debt underwriters are more likely to publish accurate or slightly pessimistic forecasts that management finally "meet or beat".

H4: Analysts affiliated with equity underwriters are less likely to publish accurate or slightly pessimistic forecasts that management finally "meet or beat".

Banking relationship is more important when the firm is a larger current or potential customer. Thus, we propose the third hypothesis.

H5: Forecasts by analysts affiliated with equity underwriters are more likely to publish accurate or slightly pessimistic forecasts that management finally "meet or beat" for larger firms.

When financial distress risk is higher, however, debt value becomes correlated with equity value, obliterating the immunity to investor relationship concerns of analysts affiliated with debt underwriters. However, this relationship may be obscured by general difficulty in valuing troubled firms, as these firms have lower earnings predictability (Das et al., 1998, Joos and Plesko, 2005). We circumvent this concern by comparing the marginal effect of financial distress on accuracy and optimism among the groups of analysts.

H6: When financial distress risk is higher, forecasts optimism and forecast errors of analysts affiliated with debt underwriters increases faster than other analysts.

We run the following regression to test our hypotheses:

$$Forecast\ Errors/Accuracy/Optimism/Guided\ Forecasts$$
$$= \beta_{0i} + \sum \beta_{mi} Dummy\ for\ affiliation_{mi} + \sum \beta_{ni} Control_{ni} + \varepsilon_i \quad (1)$$

3. Data and variable construction

3.1. Data

We obtain earnings forecasts and recommendations from the I/B/E/S database for the period from 1999 to 2016, and match them using analyst code, followed firm's CUSIP, and forecast announcement date. We eliminate duplicate earnings forecasts and recommendations made by the same analyst for the same firm on the same day. As there are much more price forecasts than recommendations, we match price forecasts and recommendations by assuming that one recommendation is valid until either another recommendation is published or 365 days pass. We further remove forecasts made less than 15 days before the announcement of the actual earnings, and forecasts made before the beginning of the financial year. We match the I/B/E/S data with daily prices and market return data from CRSP using CUSIP and date, and financial data from Compustat using CUSIP and year.

We manually decode the bank codes (variable "estimid") to obtain the name of the analyst's employer. To do this, we use I/B/E/S Price Forecast file because the bank codes in the Price Forecast file are most of the time abbreviation of the banks' names, and in this file analyst names are provided. We look up the exact names of the banks on the internet by reading profiles and career history of the top analysts at each banks in the data, notably from brokerage houses' websites, LinkedIn, TipRanks, Bloomberg profiles. There are 943 bank codes in the Price Forecast file, most of which appear only a few times in the data. We successfully decoded 149 banks into their full name. These 149 banks account for almost 95% of all observations in the Price Forecast file. We match this bank name data with earnings forecasts and recommendations.

We obtain underwriting relationship data from Thomson One Banker and match them with the analyst data using the underwriter's name. While most other studies assume that an underwriting relationship lasts for 5 years after the offering, we take a stricter stand. We assume that the relationship only stretches over a period of two years after date of the security issue, which significantly reduces the number of relationships observed. We think that two years is a reasonable time window to test our hypotheses for several reasons. First, the portfolio turnover ratio of non-index mutual funds in the U.S. is roughly 50%, which implies an investment holding period of 2 years (Rowley and Dickson, 2012). Second, large investors participating in equity issues are very often restricted from selling their shares in the locking periods of one years. Our hypothesis about the analysts affiliated with equity underwriters posits that they care about the aftermarket of the shares they have underwritten, and thus they may have strong incentives to push stock price within that time frame to please the investors who have taken part in the issue.

For the purpose of the tests, following previous literature, we keep only the latest forecasts of a year. We keep only forecasts that are revised at least 3 times during the year to restrain our sample to those of more active, enduring stock coverage. We further trim the data by eliminating extreme observations in the 1st and the 100th percentiles of signed forecast errors. All this procedure culminates in a sample of 249,545 analyst-firm-year observations over the period from 1999 to 2016, of 9,437 analysts and 7,636 firms.

3.2. Dependent variables

We use different measures of forecast accuracy to ensure robustness of the tests. We use variable *AFE*, *PMAFE* and *ACCUR* as surrogates for earnings forecast errors and earnings forecast accuracy. We use variable *OTM1 and SFE* to proxy for optimism. Variable *GUIDED* indicates collusion between the analysts and the firms to manage forecasts at the levels that management can "meet or beat".

First, we measure signed earnings forecast errors (*SFE*) as the difference between year-end earnings forecasts and actual earnings, deflated by the stock price at the day of the forecast is made.

$$SFE = \frac{E_{actual} - E_{forecast}}{P_0}$$

Second, we measure absolute earnings forecast errors (*AFE*) as the absolute value of *SFE* (Jacob, 1997, Mikhail et al., 1997, Mikhail et al., 2003, Drake and Myers, 2011).

$$AFE = \frac{\left|E_{actual} - E_{forecast}\right|}{P_0}$$

These two measures are intuitive, as users of a report would probably judge the performance of an analyst primarily by how far the forecast is to the actual accounting earnings.

Jacob et al. (1999) criticize the use of *AFE* for being contaminated by inter-temporal changes and cross-sectional differences. Following prior literature, we correct for this by adding several control variables to capture these inter-temporal changes and cross-sectional differences, such as year dummies, industry dummies, a measure of information intensity surrounding the firm.

As alternatives, we calculate two relative measures of forecast errors. Following Clement (1999), we calculate *PMAFE* as the difference between the forecast error and mean forecast error for each firm in each year, scaled by mean *AFE*.

$$PMAFE = \frac{AFE - mean(AFE)}{mean(AFE)}$$

Following Clement and Tse (2005), we derive another relative measure of forecast accuracy (*ACCUR*). We subtract the maximum absolute forecast error for a firm in a year by absolute forecast error of each analyst-firm, and scale it by the range of absolute forecast errors. The higher this variable is, the more accurate the forecast is.

$$ACCUR = \frac{max(AFE) - AFE}{max(AFE) - min(AFE)}$$

Intuitively, a forecast is optimistic if it is higher than actual value. Thanks to informational advantage, affiliated analysts are able to precisely predict actual earnings. Therefore, they are optimistic only if they ignore their information advantage and make a forecast that is above the actual earnings. Following this argument, we measure optimism by dummy variable *OTM1*, which equals one if a forecast is higher than actual earnings. Nevertheless, it is widely agreed in the literature to define an optimistic forecast as one above the consensus forecast (Hong and Kubik, 2003, Cowen et al., 2006, Guan et al., 2012). We use an alternative dummy variable *OTM2*, which take the value of one if the forecast is higher than the median forecast for a firm in a given year.

Similar to Roychowdhury (2006), we record guided forecasts by dummy variable *GUIDED*, which takes the value of 1 if actual earnings minus forecasted earnings is 0 or between 0 and 10 cents when actual earnings are positive. This variable indicates forecasts that are suspected to be strategically coordinated with the firm's earnings, so that actual reported earnings can "meet or beat" forecasts.

3.3. Independent variables

Our main independent variables of interest include two dummies: *DU*, *EU* and, which respectively receive the value of one if the analyst is affiliated with one of the followed firm's debt underwriters and equity underwriters respectively, and zero otherwise. Because we are concerned with the difference between analysts affiliated with debt underwriters and equity underwriters, a *DU* and *EU* must not take the value of one at the same time. We create another variable, *EDU*, which takes the value of one if an analyst's employer underwriters both debt and equity of the followed firm, and zero otherwise.

We consult the literature to add relevant control variables into our model. Mikhail et al. (1997), followed by many other studies, suggest that analysts' individual characteristics, could potentially affect forecast accuracy. *GEXPER* is the analyst's general experience, measured by the number of years the analyst has been in our data to the day of the forecast. *FEXPER* is the analyst's firm-specific experience, measured by the number of years the analyst has covered the followed firm in our data to the day of the forecast. *INDCONC* is the analyst's industry concentration, calculated by the number of firm that analyst cover in one industry divided by the total number of his coverage firms in a given year. *NIND* is the number of 2-digit SIC code industries an analyst covers in a given year. *NFIRM* is the number of firms an analyst covers in a given year. Lower *GEXPER*, *FEXPER*, *INDCONC* and higher *NFIRM*, *NIND* imply more forecast errors (Mikhail et al., 1997, Mikhail et al., 2003, Clement and Tse, 2005).

We account for other factors that may also affect analyst forecasts. *INFOINT* is information intensity or analyst competition surrounding a given firm, measured by the number of analysts covering that firm in a given year. *TOPBANK* is a dummy variable taking the value of one if the analyst's employer is among twenty U.S. and international large banks. The list of these banks is available upon request. Larger brokerage house may be able to make more accurate forecasts because they can attract more talented employees and have more resources. *FCAGE* is the number of days from earnings forecast announcement date to announcement of actual earnings. More distant forecasts bear more uncertainty, thus are less accurate. Mikhail et al. (2003) assert that earnings forecasts are persistent through time, we add lagged earnings forecast errors into the list of control variables. In an attempt to relate earnings forecasts and recommendation, we add *RECOM*, a discrete variable with recommendation code associated with each forecast.

Following Clement (1999), in all regressions with *PMAFE* as dependent variable, for each firm-year, independent variables *X* is replaced by *X1* calculated as follows across all analysts, except dummy independent variables and *RECOM*.

$$X1 = \frac{X - mean(X)}{mean(X)}$$

Following Clement and Tse (2005), in all regressions with *ACCUR* as dependent variable, for each firm-year, independent variables *X* is replaced by *X2* calculated as follows across all analysts, except dummy independent variables and *RECOM*.

$$X2 = \frac{X - min(X)}{max(X) - \min(X)}$$

Following Altman (1968), we calculate Altman's Z-score to reflect financial distress risk by the following formula. The lower the score is, the higher the financial distress risk is.

Z-score = 1.2*X1 + 1.4*X2 +3.3*X3 + 0.6*X4 + 1*X5

Where

X_1 = working capital / total assets.

X_2 = retained earnings / total assets.

X_3 = earnings before interest and taxes / total assets.

X_4 = market value of equity / book value of total liabilities.

X_5 = sales / total assets.

4. Results

4.1. Summary statistics

Table 1 provides some interesting statistics of signed forecast errors.

[Table 1 inserts here]

Panel A reveals that the distribution is negatively skewed, with a fatter tail on the left, as evinced by a negative skewness. This finding is consistent with other studies on over-optimism of stock analysts. Apart from the tails, however, other observations are distributed more densely around zero forecast errors, with more positive than negative forecast errors. Note that forecast errors is actual earnings subtracted by forecasts. It means that most analysts are not optimistic, but some of them are extremely so. Mean *OTP1* verifies that only 35% of all forecasts are optimistic.

Panel B shows that analysts affiliated with equity underwriters are most likely to publish optimistic forecasts, as indicated by higher mean *OTP1*. Moreover, the level of their optimism is much higher than other analysts, as indicated by mean *SFE*. They also have much larger deviation in their forecast errors and are least likely to publish supposedly guided forecasts. Analysts affiliated with debt underwriters are completely the opposite. They are less optimistic, more precise, have less deviation in forecast errors, and are more likely to publish slightly pessimistic forecasts, those that the management would finally “meet or beat”. GUIDED indicates that 42% of all forecasts are perfectly correct or smaller than actual earnings by less than 10 cents of a dollar.

Panel C shows that analysts affiliated with equity underwriters are not only generous in their forecasts, but also in their recommendation. *RECOM* is a ordinal variable which takes the value of 1, 2, 3, 4, 5 corresponding to recommendation strong buy, buy, hold, sell, strong sell, respectively. As indicated by mean recommendation code value, analysts affiliated with equity underwriters are most favorable in their recommendation for every level of forecast errors, while those affiliated with debt underwriters appear much more conservative. In our sample, less than 50% of all recommendations by analysts affiliated with debt underwriters and unaffiliated analysts are buy or strong buy, and more than 50% are hold, sell and strong sell. These percentages in analysts affiliated with equity underwriters are almost 2-to-1, 63% and 37%, respectively. There may be two possible explanations for this large discrepancy. First, banks may actively select more good firms than bad firms to offer equity underwriting services. This is supported by the statistics of Z-scores, which shows that buy recommendations are issued to more financially secured firms. This hypothesis, however, does not explain why debt underwriters do not apply a similar selection bias. Second, as I/B/E/S data are built on voluntary disclosures by brokerage houses, equity underwriters may be less willing than debt underwriters to publish or disclose unfavorable recommendations. This second hypothesis is indeed consistent with our conjecture that the analyst conflict of interest is more security-specific (i.e. investor relationship) than firm-specific (banking relationship).

Traditional view on analyst conflict of interest does not distinguish between analysts affiliated with equity underwriters and debt underwriters. Table 1 shows, however, that analysts affiliated with debt underwriters are able to produce significantly more precise and less optimistic earnings forecasts than other analysts, probably because they have inside information and private contact with managers of the firms. Although analysts affiliated with equity underwriters also possess those advantages, but are unable to translate them into superior accuracy. These statistics supports our hypothesis that their interests are conflicted in a different way than their counterparts at debt underwriters.

Figure 2 shows density distribution of signed forecast errors for analysts affiliated with equity underwriters and debt underwriters. As can be seen, forecasts by analysts affiliated with debt underwriters are clustered more around zero, in the area immediately left and right of zero. That is the area of forecasts where the management can “meet or beat”, or at least miss just marginally. Whereas, forecasts by analysts affiliated with equity underwriters are similarly concentrated in the area right of zero, that is slightly pessimistic forecasts managements would finally beat, but also very often deviate largely from zero in the two fat tails. These observations are consistent with our conjecture about the behavior of affiliated analysts.

[Figure 2 inserts here]

Table 2 provides summary statistics of key variables. Compared to previous studies, our samples have roughly the same level of forecast errors. For example, in Clement et al. (2007)'s sample, absolute forecast errors *not scaled* by stock price has 1^{st}, 2^{nd} and 3^{rd} quartile value of 0.01, 0.05 and 0.17 respectively. Those of our sample are 0.02, 0.05 and 0.13, respectively. Note that in this paper we define *AFE* as absolute forecast errors *scaled* by stock price. That is why median and mean *AFE* is only 0.002 and 0.007, respectively. This is probably due to our sample selection procedure, where extreme *AFE* are removed, that the 1^{st} and 3^{rd} quartiles are closer to the median. Clement (1999) and Clement et al. (2007) have the samples with median *PMAFE* of -0.08 and -0.20, respectively. Ours is -0.12. Clement and Tse (2003) sample has a mean *ACCUR* of 0.58, while ours is 0.64.

The number of sell and strong sell recommendations is by far smaller than the number of buy and strong buy recommendation, accounting for roughly 6% of all observations, while buy recommendation and hold recommendation account for 50.5% and 43.5%, respectively. This dipropionate distribution is reflected in mean *RECOM*. Lin and McNichols (1998) and Malloy (2005) argue that a hold recommendation may actually mean sell.

[Table 2 inserts here]

Mean general experience and mean firm-specific experience are slightly higher than other studies, obviously because our sample spreads through a longer period. Mean *FCAGE* indicates that on average, the analyst makes the last forecast almost 3 months before announcement date. *TOPBANK* shows that the top 20 banks account for 35% of all forecasts. An analyst on average covers 17 firms and 2.6 industries, as indicated by *NIND* and *NFIRM*.

4.2. Forecast accuracy

Table 3 shows selected results for our multivariate tests of the relationships between types of affiliations and earnings forecast accuracy. We use three proxies for forecast accuracy: *AFE*, *PMAFE* and *ACCUR*. Note that *AFE* is absolute forecast errors, while *PMAFE* (*ACCUR*) are relative measures of forecast errors (accuracy). That means *ACCUR* is negatively correlated with *AFE* and *PMAFE*. Regression coefficients are thus expected to have opposite signs. Our main independent variables of interests are *DU*, *EU*. We use control variables that are commonly used in previous studies, and time and industry dummies. Following prior studies, the calculation of independent variables is different in each regression depending on the dependent variable. Variable construction details are provided in Part 3.

Consistently in all regressions, analysts affiliated with debt underwriters make smaller forecast errors and are more accurate than unaffiliated analysts, while analysts affiliated with equity underwriters make more errors and are less accurate. The statistical significance is weakest in regression (2), at 5% level of significance, but strong in (1) and (3).

While all affiliated analysts have superior access to information, only analysts affiliated with debt underwriters exhibit superior forecast accuracy. Equity affiliated analysts are even less accurate than unaffiliated analysts. These results support our first three hypotheses.

[Table 3 inserts here]

The coefficients of *RECOM* show that analysts are less accurate in less favorable recommendations. Unfavorable recommendations may be indicative of deteriorating relationship between the analyst and the firm, thus analysts may be less able or willing to collide with the firm to publish highly accurate forecasts.

Mikhail et al. (1997) assert that forecast accuracy increases with experience as suggested by a learning-by-doing model. Mikhail et al. (2003) claim that the superior accuracy of experienced analysts is attributable to the fact that they are less dependent on past forecast errors. As expected, Table 3 shows that there is a consistently negative correlation between *GEXPER* and forecast errors, and accordingly a positive correlation between *GEXPER* and forecast accuracy. The effect of *FEXPER*, however, is not clear. This can be because GEXPER and FEXPER has relatively high correlation (0.57). The coefficients of lagged *AFE,* lagged *PMAFE* and lagged *ACCUR* are all positive and smaller than one, indicating persistency in forecast errors and accuracy (Mikhail et al., 2003).

The coefficients on information intensity (*INFOINT)* are negative and highly significant in regression (1), suggesting that forecast errors decrease in response to the availability of information (Mikhail et al., 1997) or analyst competition (Lys and Soo, 1995). This is consistent with prior literature. The coefficient of *INDCONC* is not significant in the regressions (1). Mikhail et al. (1997) also observe inconsistency of this variable. Consistent with prior studies (Mikhail et al., 1997, Clement, 1999), the coefficients of *FCAGE* shows that later forecasts are more accurate (Mikhail et al., 1997). Analysts at top banks appear to be less accurate, as indicated by the coefficients of *TOPBANK*. Jacob (1997) and Clement (1999) shows that analysts' forecast accuracy improves with employer size. The disagreement between our results and prior literature maybe due to difference in data, variable construction and model specification. Figure 2 intuitively show that this inaccuracy of analysts at top banks is likely due to their forecast conservatism.

Other control variables that have been used in the literature to measure task complexity, such as total number of firms (*NFIRM*) or industries (*NIND*) followed by an analyst (Clement, 1999). Both the number of industries and the number of firms covered (*NFIRM*), covered shows a negative effect on forecast accuracy.

In summary, Table 3 demonstrates that there are material differences between analysts affiliated with debt underwriters and those affiliated with equity underwriters in their forecast errors. While both benefit from information advantage and afflicted by banking relationship concern, only analysts who work at debt underwriters have the incentives to transform that advantage into superior forecast accuracy. Whereas, analysts affiliated with equity underwriter very often deviate largely from the desirable accurate forecasts. This discrepancy cannot be explained by the popular view that analysts forgo forecast accuracy to court future business from issuing firms but is consistent with the view that analysts are more concerned with the aftermarket stock performance, as we have previously argued.

4.3. *Forecast optimism*

Table 4 exposes the source of superior accuracy of analysts affiliated with debt underwriters, and the source of errors made by analysts affiliated with equity underwriters observed previously. Because the dependent variables in (1) and (4) are binary, probit regressions are used. Otherwise, we use pooled OLS in regression (2) and regression (3).

[Table 4 inserts here]

In regression (1), the dependent variable, which identifies optimistic forecasts, takes the value of one if the forecast is higher than actual value and zero otherwise. Interestingly, analysts affiliated with equity underwriters are significantly more likely to publish these optimistic forecasts. Regression (2) indicates that among these optimistic forecasts, the level of optimism is highest in those published by analysts affiliated with equity underwriters, and least so in analysts affiliated with debt underwriters. Regression (3) shows, however, that in pessimistic forecasts, analysts affiliated with equity underwriters are most likely to be extremely pessimistic.

These three regressions represent what we previously observed in Figure 2: analyst affiliated with debt underwriters are so accurate because they are less optimistic, and mostly stay in the area around zero forecast errors, such forecast area where the management of the followed firms would finally "meet or beat". Note that while analysts affiliated with equity underwriters deviate most often from the desirable accurate forecast area, that does not mean they all do. As can be observed in Figure 2, most of them are still clustered in the area right below zero. Analysts affiliated with debt underwriters and equity underwriters both enjoy access to management and information advantage. They both have the incentives to maintain hard-earned banking relationship with the followed firms. Why are they behaving differently? The reason must be that they are affected by another type of conflict, i.e. the investor relationship concern. These findings support our hypotheses.

It is widely agreed in the literature to define an optimistic forecast as one above the consensus forecast (Hong and Kubik, 2003, Cowen et al., 2006, Guan et al., 2012). We use an alternative dummy variable *OTM2*, which take the value of one if the forecast is higher than the median forecast for a firm in a given year. However, it doesn't show any relationship with underwriting affiliations.

4.4. Forecast accuracy and optimism in relation with financial distress risk

Previously we argued that analysts affiliated with debt underwriters are concerned with the debt their employers underwrite, and their indifference about equity makes them more accurate than equity underwriters. That remains true as long as debt value is not correlated with firm performance and stock price. However, this advantage will be jeopardized if debt value becomes correlated with firm performance and stock price. This happens when firms get closer to financial distress. The higher the probability of financial distress, the stronger debt value and firm performance are correlated. This makes the concern in debt becomes a concern in equity. Analysts affiliated with equity underwriters and unaffiliated analysts have no reason to be affected by financial distress as much as analysts at debt underwriters.

We therefore predict that higher financial distress is going to have larger positive effect on forecast errors and optimism of analysts at debt underwriters than for other analysts. We measure financial distress risk by Altman's Z-scores (*ZSCR*). Lower *ZSCR* indicates higher financial distress risk. We use interactions between affiliation dummies and *ZSCR* to test the differential effect of *ZSCR* on each affiliation type.

In regression (1), the coefficient of *ZSCR* shows that for the benchmark group of unaffiliated analysts, the effect of financial distress risk on forecast errors is unclear. However, regression (2) shows that lower *ZSCR*, meaning higher financial distress risk, is associated with higher levels of optimism in optimistic forecasts.

The interaction between underwriting affiliation and financial distress risk shows that when financial distress risk increases (i.e. *ZSCR* decreases) forecast errors and optimism increase significantly faster in analysts affiliated with debt underwriters compared to analysts affiliated with equity underwriters and unaffiliated analysts. These differences are all statistically significant and consistent in all regression (1), (2) and (3). The coefficients on interaction terms between *EU* and *ZSCR* in regression (1) and (3) imply that higher financial distress risk makes analysts affiliated with equity underwriters less accurate, too, but to much a lesser extent than analysts affiliated with debt underwriters, as can be seen by much smaller magnitude of the coefficients. In unreported tests where we make direct comparison of the coefficient between analysts affiliated with debt underwriters and equity underwriters, the coefficients are statistically different in the direction that financial distress risk affect forecasts accuracy and optimism of the analysts affiliated with debt underwriters much more than analysts affiliated with equity underwriters.

[Table 5 inserts here]

Up to this point, we can summarize our results as follows: analysts affiliated with debt underwriters are more accurate and less optimistic than other analysts in their earnings forecasts. Moreover, the quality of their forecasts deteriorates with higher probability of financial distress. Thus, the conflicts of interest effect is not firm-specific but security-specific. Analysts at debt underwriters are generally unaffected by the security-specific conflict of interest. Does that mean the firm-specific conflicts of interest are irrelevant? In what follows, we show that it may not be the case.

4.5. Guided forecasts

Table 6, model (1) demonstrates that analysts affiliated with debt underwriters are significantly more likely than others to publish earnings that are just slightly below actual earnings. The threshold used in this regression to define presumable “guided” estimates is 10 cent of a dollars. Intriguingly, analysts affiliated with equity underwriters are even less likely than unaffiliated analysts to issue guided forecasts. This again supports our conjecture that they are conflicted not only by the concern of maintaining cordial relationship with the firms, at least not as much as unaffiliated analysts and analysts affiliated with debt underwriters.

[Table 6 inserts here]

Regression (2) reveals the relationship between analyst affiliation and financial distress risk. For analysts affiliated with debt underwriters, the higher the financial distress risk of the firm, the less likely they are to publish forecasts that are accurate and slightly below actual earnings. This is consistent with the findings in Table 5, where analysts affiliated with debt underwriters are found to be more optimistic, less accurate when financial distress risk is higher, and supports our hypotheses.

Understandably, analysts with more experience are more likely to be able to connect themselves with the followed firms, thanks to their stronger standing in the industry. Analysts at larger banks tend to make less guided forecasts. This is consistent with previous results that they appear more conservative and less accurate. Perhaps because of their employers' larger size, they feel less tempted to collide with the followed firms.

Previously, we argue that analysts affiliated with equity underwriters deviate more from the desirable accurate forecasts because they have concerns other than maintaining banking relationship. If, however, the firm is large enough, it may have to market power to lure the analysts into their forecast management scheme. Analysts would be more tempted to sacrifice other concerns and more cooperative. Regression (3) indeed indicates that there are more accurate, supposedly guided forecasts for larger firms. Moreover, analysts affiliated with equity underwriters are much more likely to publish these guided forecasts when firm size gets larger.

In conclusion, our empirical results illustrate the behavioral difference of analysts affiliated with debt underwriters and equity underwriters. This difference cannot be explained by the traditional banking relationship hypothesis which has been well-established in the literature. The investor relationship conflicts of interest are evident given the relationship between accuracy, optimism and financial distress risk.

Nevertheless, examination of guided forecasts and firm size implies that superior accuracy is not necessarily caused by higher objectivity, but more collusion.

5. Conclusion

We present some interesting results that have not been observed in the literature. By showing the differential accuracy and optimism between analysts affiliated with debt underwriters and equity underwriters, we reckon that the relationship hypothesis widely cited in the literature is flawed. We propose an alternative framework to understand affiliated analysts' conflicts of interest. In our framework, we introduce investor relationship concern, which, based on the empirical data, dominate the banking relationship concern. We also point out that optimism may not as much a sign of analyst-firm collusion as extraordinary precision.

References

Altman, E. I. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance,* 23**,** 589-609.

Asquith, P., Mikhail, M. B. & Au, A. S. 2005. Information content of equity analyst reports. *Journal of financial economics,* 75**,** 245-282.

Bajo, E., Chemmanur, T. J., Simonyan, K. & Tehranian, H. 2016. Underwriter networks, investor attention, and initial public offerings. *Journal of Financial Economics,* 122**,** 376-408.

Bartov, E., Givoly, D. & Hayn, C. 2002. The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics,* 33**,** 173-204.

Bernhardt, D. & Campello, M. 2007. The Dynamics of Earnings Forecast Management*. *Review of Finance,* 11**,** 287-324.

Beyer, A. 2008. Financial analysts' forecast revisions and managers' reporting behavior. *Journal of Accounting and Economics,* 46**,** 334-348.

Bradshaw, M. T. 2011. Analysts' forecasts: what do we know after decades of work?

Bradshaw, M. T., Richardson, S. A. & Sloan, R. G. 2001. Do Analysts and Auditors Use Information in Accruals? *Journal of Accounting Research,* 39**,** 45-74.

Burgstahler, D. & Eames, M. 2006. Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises. *Journal of Business Finance & Accounting,* 33**,** 633-652.

Chen, T. & Martin, X. 2011. Do Bank-Affiliated Analysts Benefit from Lending Relationships? *Journal of Accounting Research,* 49**,** 633-675.

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

Clement, M. B., Koonce, L. & Lopez, T. J. 2007. The roles of task-specific forecasting experience and innate ability in understanding analyst forecasting performance. *Journal of Accounting & Economics,* 44**,** 378-398.

Clement, M. B. & Tse, S. Y. 2003. Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters? *The Accounting Review,* 78**,** 227-249.

Clement, M. B. & Tse, S. Y. 2005. Financial Analyst Characteristics and Herding Behavior in Forecasting. *The Journal of Finance,* 60**,** 307-341.

Cowen, A., Groysberg, B. & Healy, P. 2006. Which types of analyst firms are more optimistic? *Journal of Accounting & Economics,* 41**,** 119-146.

Das, S., Levine, C. B. & Sivaramakrishnan, K. 1998. Earnings predictability and bias in analysts' earnings forecasts. *Accounting Review,* 73**,** 277.

Dechow, P. M., Hutton, A. P. & Sloan, R. G. 2000. The Relation between Analysts' Forecasts of Long-Term Earnings Growth and Stock Price Performance Following Equity Offerings*. *Contemporary Accounting Research,* 17**,** 1-32.

Degeorge, F., Derrien, F. & Womack, K. L. 2007. Analyst hype in IPOs: explaining the popularity of bookbuilding. *The Review of Financial Studies,* 20**,** 1021-1058.

Degeorge, F., Xe, Ois, Patel, J. & Zeckhauser, R. 1999. Earnings Management to Exceed Thresholds. *The Journal of Business,* 72**,** 1-33.

Derrien, F. & Kecskés, A. 2013. The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. *The Journal of Finance,* 68**,** 1407-1440.

Drake, M. & Myers, L. 2011. Analysts' accrual-related over-optimism: do analyst characteristics play a role? *Review of Accounting Studies,* 16**,** 59-88.

Easterwood, J. C. & Nutt, S. R. 1999. Inefficiency in Analysts' Earnings Forecasts: Systematic Misreaction or Systematic Optimism? *The Journal of Finance,* 54**,** 1777-1797.

Ellul, A. & Panayides, M. 2018. Do financial analysts restrain insiders' informational advantage? *Journal of Financial and Quantitative Analysis***,** 1-39.

Graham, J. R., Harvey, C. R. & Rajgopal, S. 2005. The economic implications of corporate financial reporting. *Journal of Accounting and Economics,* 40**,** 3-73.

Guan, Y., Lu, H. & Wong, M. H. F. 2012. Conflict-of-Interest Reforms and Investment Bank Analysts' Research Biases. *Journal of Accounting, Auditing & Finance,* 27**,** 443-470.

Haushalter, D. & Lowry, M. 2011. When Do Banks Listen to Their Analysts? Evidence from Mergers and Acquisitions. *Review of Financial Studies,* 24**,** 321-357.

Hong, H. & Kubik, J. D. 2003. Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *The Journal of Finance,* 58**,** 313-351.

Hugon, A., Lin, A.-P. & Markov, S. 2016. Do Equity Analysts Benefit from Access to High Quality Debt Research?

Hwang, B.-H., Liberti, J. M. & Sturgess, J. 2018. Information sharing and spillovers: Evidence from financial analysts. *Management Science*.

Jacob, J. 1997. Discussion of Do Security Analysts Improve Their Performance with Experience? *Journal of Accounting Research,* 35**,** 159-166.

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

James, C. & Karceski, J. 2006. Strength of analyst coverage following IPOs. *Journal of financial Economics,* 82**,** 1-34.

Joos, P. & Plesko, G. A. 2005. Valuing Loss Firms. *Accounting Review,* 80**,** 847-870.

Kelly, B. & Ljungqvist, A. 2012. Testing asymmetric-information asset pricing models. *The Review of Financial Studies,* 25**,** 1366-1413.

Lin, H.-W. & Mcnichols, M. F. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics,* 25**,** 101-127.

Ljungqvist, A., Marston, F. & Wilhelm, W. J. 2006. Competing for Securities Underwriting Mandates: Banking Relationships and Analyst Recommendations. *The Journal of Finance,* 61**,** 301-340.

Lys, T. & Soo, L. G. 1995. Analysts' Forecast Precision as a Response to Competition. *Journal of Accounting, Auditing & Finance,* 10**,** 751-765.

Malloy, C. J. 2005. The Geography of Equity Analysis. *The Journal of Finance,* 60**,** 719-755.

Matsumoto, D. A. 2002. Management's Incentives to Avoid Negative Earnings Surprises. *Accounting Review,* 77**,** 483-514.

Mayo, M. 2012. Exile on Wall Street: One Analyst's Fight to Save the Big Banks from Themselves. *John Wiley & Sons, Inc*.

Michaely, R., Michaely, R., Womack, K. L. & Womack, K. L. 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies,* 12.

Mikhail, M. B., Walther, B. R. & Willis, R. H. 1997. Do Security Analysts Improve Their Performance with Experience? *Journal of Accounting Research,* 35**,** 131-157.
Mikhail, M. B., Walther, B. R. & Willis, R. H. 2003. The effect of experience on security analyst underreaction. *Journal of Accounting and Economics,* 35**,** 101-116.
O'brien, P. C., Mcnichols, M. F. & Hsiou-Wei, L. I. N. 2005. Analyst Impartiality and Investment Banking Relationships. *Journal of Accounting Research,* 43**,** 623-650.
Quinn, P. J. 2018. Shifting corporate culture: executive stock ownership plan adoptions and incentives to meet or just beat analysts' expectations. *Review of Accounting Studies***,** 1-32.
Raedy, J. S., Shane, P. & Yang, Y. 2006. Horizon-Dependent Underreaction in Financial Analysts' Earnings Forecasts*. *Contemporary Accounting Research,* 23**,** 291-322.
Rowley, J. J. J. & Dickson, J. M. 2012. Mutual funds - like ETFs - have trading volume. *Vanguard research.* The Vanguard Group.
Roychowdhury, S. 2006. Earnings management through real activities manipulation. *Journal of Accounting and Economics,* 42**,** 335-370.

Figure 1

The types of forecasts and their uses

Forecast error (actual – forecast)

+ *(pessimistic)* 0 – *(optimistic)*

Pessimistic forecast. Undesirable.

Accurate forecast. Preferred by both the analyst and the firm. Slightly pessimistic forecasts are most preferred by the firm's management.

Optimistic forecast. Used by equity underwriters to support stock price.

Table 1: Statistics of Signed Forecast Errors

SFE= (actual earnings – forecast)/stock price; OPT1=1 if SFE<0 and OPT1=0 otherwise; SUSPECT=1 if SFE >=0 & SFE<=0.1 and SUSPECT=0 otherwise. RECOM takes the value of 1, 2, 3, 4, 5 corresponding to strong buy, buy, hold, sell, strong sell recommendation, respectively.

Panel A: Signed forecast errors (SFE)

Percentiles	
1%	-0.08135
5%	-0.01942
10%	-0.00778
25%	-0.00111
50%	0.000445
75%	0.002462
90%	0.007592
95%	0.014416
99%	0.042339
Number of observations	249,545
Mean	-0.00095
Skewness	-4.32625
Mean OPT1	0.350915

Panel B: Mean OPT1, SFE and SUSPECT by types of analysts

Analyst affiliation	OPT1	SFE	Std. Dev. of SFE	GUIDED
DU	0.342682	-0.0007	0.014793	0.446154
EU	**0.392909**	**-0.0016**	**0.020977**	**0.339126**
ED	0.43584	-0.0026	0.021765	0.308265
UNAF	0.346807	-0.0009	0.017673	0.429254
All	0.350915	-0.0009	0.017821	0.422601

Panel C: Mean RECOM by types of affiliations and ranges of signed forecast errors

	DU	**EU**	ED	UNAF	All
SFE<=-0.02	2.56	**2.26**	2.61	2.49	2.48
-0.02<SFE<=-0.01	2.57	**2.13**	2.35	2.37	2.35
-0.01<SFE<0.01	2.41	**2.13**	2.27	2.32	2.32
0.01<=SFE<0.02	2.51	**2.27**	2.31	2.43	2.42
0.02<=SFE	2.66	**2.33**	2.55	2.47	2.47
Total	2.43	**2.16**	2.31	2.34	2.34

Figure 2: Density of signed forecast errors

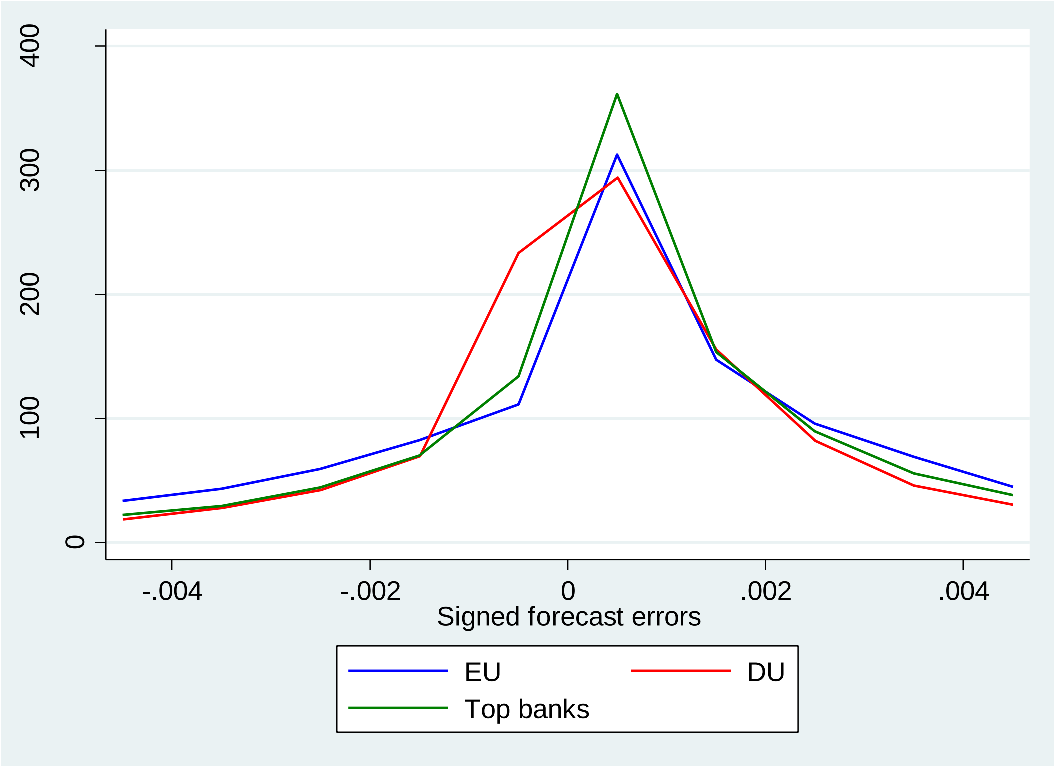

Table 2: Statistics of key variables

AFE is absolute forecast errors. *PMAFE* is relative forecast errors. *ACCUR* is relative forecast accuracy. *DU*, *EU* and *EDU*, are affiliation dummies, respectively receive the value of one if the analyst is affiliated with one of the followed firm's debt underwriters, equity underwriters, or underwriters that participate in both debt and equity issues. *RECOM* is recommendation. *GEXPER* is general experience. *FEXPER* is firm-specific experience. *FCAGE* is the number of days from forecast announcement to announcement of actual earnings. *TOPBANK* is bank size dummies, which takes the value of oone if the analyst's employer is one of twenty top banks and zero otherwise. *INFOINT* is the followed firm's information intensity. *INDCONC* is the analyst's industry concentration. *NFIRM* is the number of firms the analyst follows in a given year. *NIND* is the number of industries the analyst follows in a given year.

Variable	Obs.	Mean	Std. Dev.	Min	Max
AFE	249,545	0.006993	0.01642	0	0.20113
PMAFE	248,528	-0.02005	0.86669	-1	21.69952
ACCUR	241,488	0.635887	0.35622	0	1
RECOM	249,545	2.335194	0.929754	1	5
DU	249,545	0.058867	0.235376	0	1
EU	249,545	0.063183	0.243292	0	1
ED	249,545	0.016145	0.126035	0	1
GEXP	249,545	6.988323	4.5101	0	17
FEXP	249,545	3.528634	3.249631	0	17
FCAGE	249,545	85.7117	42.77648	15	441
TOPBANK	249,545	0.350366	0.477085	0	1
INFOINT	249,545	18.93245	11.12387	1	69
INDCONC	249,545	0.491836	0.287479	0.009524	1
NIND	229,072	2.625148	1.732027	1	13
NFIRM	249,545	17.49427	8.682753	1	108
ZSCORE	175,774	5.300751	184.753	-109.891	38709.91
AT	229,033	8.124936	1.957824	-0.86038	14.80599

Table 3
Earnings forecast errors

This table presents selected results from the following regression:

$$Forecast\ Errors/Accuracy = \beta_{0i} + \sum \beta_{mi} Dummy\ for\ affiliation_{mi} + \sum \beta_{ni} Control_{ni} + \varepsilon_i$$

AFE is absolute forecast errors. *PMAFE* is relative forecast errors. *ACCUR* is relative forecast accuracy. *DU*, *EU* and *EDU*, are affiliation dummies, respectively receive the value of one if the analyst is affiliated with one of the followed firm's debt underwriters, equity underwriters, or underwriters that participate in both debt and equity issues. *RECOM* is recommendation. *GEXPER* is general experience. *FEXPER* is firm-specific experience. *FCAGE* is the number of days from forecast announcement to announcement of actual earnings. *TOPBANK* is the bank's size. *INFOINT* is the followed firm's information intensity. *INDCONC* is the analyst's industry concentration. *NFIRM* is the number of firms the analyst follows in a given year. *NIND* is the number of industries the analyst follows in a given year. Note that the independent variables are calculated differently according to the dependent variable used. Details of variable construction are specified in Part 3.

VARIABLES	(1) AFE	(2) PMAFE	(3) ACCUR
DU	-0.000757***	-0.0251**	0.0122***
	(0.000191)	(0.00998)	(0.00443)
EU	0.00102***	-0.00381	-0.0125**
	(0.000271)	(0.0100)	(0.00548)
EDU	0.000706	0.0177	0.00923
	(0.000471)	(0.0219)	(0.00951)
Lag(dep.var)	0.295***	0.159***	0.105***
	(0.0140)	(0.0115)	(0.00513)
RECOM	0.000737***	0.0117***	-0.00513***
	(6.33e-05)	(0.00285)	(0.00131)
GEXPER	-4.22e-05***	-0.0276***	0.0338***
	(1.44e-05)	(0.00816)	(0.00400)
FEXPER	-8.88e-05***	0.00929*	-0.00722*
	(1.88e-05)	(0.00549)	(0.00413)
FCAGE	2.71e-05***	0.371***	-0.118***
	(1.73e-06)	(0.0139)	(0.00453)
TOPBANK	-6.59e-05	0.0428***	-0.00721***
	(0.000104)	(0.00657)	(0.00263)
INFOINT	-0.000134***		
	(1.06e-05)		
INDCONC	0.000295		
	(0.000340)		
NFIRM		-0.0107	-0.0163***
		(0.00934)	(0.00420)
NIND		-0.0302***	-0.00993***
		(0.00725)	(0.00347)
Year dummies	Yes		
Industry dummies	Yes		
Constant	0.0100***	-0.0557***	0.648***
	(0.00188)	(0.00710)	(0.00564)
Observations	123,450	122,872	108,146
R-squared	0.134	0.063	0.034

Firm-clustered, robust standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Table 4

Optimism

This table presents selected results from the following probit regression:
$Optimism/SFE = \beta_{0i} + \sum \beta_{mi} Dummy\ for\ affiliation_{mi} + \sum \beta_{ni} Control_{ni} + \varepsilon_i$
OTMS1 and *OTMS2* are two dummy surrogates of optimism. *DU, EU* and *EDU*, are affiliation dummies, respectively receive the value of one if the analyst is affiliated with one of the followed firm's debt underwriters, equity underwriters, or underwriters that participate in both debt and equity issues. *RECOM* is recommendation. *GEXPER* is general experience. *FEXPER* is firm-specific experience. *FCAGE* is the number of days from forecast announcement to announcement of actual earnings. *TOPBANK* is the bank's size. *INFOINT* is the followed firm's information intensity. *INDCONC* is the analyst's industry concentration. *INDCONC* is the analyst's industry concentration.

VARIABLES	(1) OTM1	(2) SFE	(3) SFE	(4) OTM2
		SFE<0	*SFE>=0*	
DU	-0.0134	0.000946*	-0.000959***	-0.0131
	(0.0193)	(0.000512)	(0.000163)	(0.0125)
EU	0.0504***	-0.00173***	0.00110***	-0.0107
	(0.0177)	(0.000611)	(0.000242)	(0.0112)
EDU	0.102***	-0.00172*	0.000476	0.0241
	(0.0335)	(0.00102)	(0.000381)	(0.0227)
Lag(dep.var)		0.204***	-0.0135	
		(0.0224)	(0.0102)	
RECOM	0.0119***	-0.00147***	0.000479***	-0.0303***
	(0.00424)	(0.000155)	(5.07e-05)	(0.00319)
GEXPER	-0.00738***	5.10e-05	-2.79e-05**	-0.00298***
	(0.00113)	(3.59e-05)	(1.31e-05)	(0.000891)
FEXPER	0.000699	0.000186***	-7.67e-05***	0.00253**
	(0.00178)	(4.91e-05)	(1.68e-05)	(0.00108)
FCAGE	0.00156***	-4.07e-05***	1.20e-05***	0.000786***
	(0.000107)	(3.57e-06)	(1.18e-06)	(8.30e-05)
INFOINT	-0.00933***	0.000267***	-0.000119***	0.000521
	(0.000874)	(2.85e-05)	(8.10e-06)	(0.000335)
INDCONC	-0.0167	0.000459	0.000887***	0.00889
	(0.0265)	(0.000878)	(0.000270)	(0.0123)
TOPBANK	-0.0370***	0.000201	0.000145	-0.000987
	(0.00761)	(0.000266)	(9.13e-05)	(0.00655)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	0.157	-0.0168***	0.00793***	-0.0471
	(0.126)	(0.00298)	(0.00258)	(0.112)
Observations	229,071	42,671	80,779	229,071
R-squared		0.107	0.077	

*Firm-clustered, robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 5

Analyst affiliation and financial distress risk

This table presents selected results from the following probit regression:
$Forecast\ errors/Accuracy/Optimism = \beta_{0i} + \sum \beta_{mi} Dummy\ for\ affiliation_{mi} * ZSCR + \sum \beta_{ni} Control_{ni} + \varepsilon_i$
AFE is absolute forecast errors. *SFE is signed forecast errors*. *RECOM* is recommendation. *DU*, *EU* and *EDU*, are affiliation dummies, respectively receive the value of one if the analyst is affiliated with one of the followed firm's debt underwriters, equity underwriters, or underwriters that participate in both debt and equity issues. *ZSCR* is Atman's Z-score. *DU#ZSCR* is the interaction term between *DU* and *ZSCR*. *EU#ZSCR* is the interaction term between *EU* and *ZSCR*. *EDU#ZSCR* is the interaction term between *EDU* and *ZSCR*. *GEXPER* is general experience. *FEXPER* is firm-specific experience. *FCAGE* is the number of days from forecast announcement to announcement of actual earnings. *TOPBANK* is the bank's size. *INFOINT* is the followed firm's information intensity. *INDCONC* is the analyst's industry concentration.

VARIABLES	(1) AFE	(2) SFE	(3) SFE
		SFE<0	*SFE>=0*
DU	0.000750	-0.000869	0.000802
	(0.000498)	(0.00129)	(0.000552)
EU	0.00192***	-0.00118	0.00180***
	(0.000399)	(0.000964)	(0.000349)
EDU	0.00301***	-0.00381*	0.00324***
	(0.000938)	(0.00208)	(0.000791)
ZSCR	-1.01e-07	0.000672***	3.93e-07*
	(3.92e-07)	(0.000110)	(2.15e-07)
DU#ZSCR	-0.000552***	0.000960***	-0.000583***
	(0.000134)	(0.000349)	(0.000151)
EU#ZSCR	-0.000212***	-0.000200	-0.000149***
	(5.24e-05)	(0.000146)	(4.50e-05)
EDU#ZSCR	-0.00167***	0.00249***	-0.00151***
	(0.000358)	(0.000763)	(0.000311)
Lag(dep.var)	0.316***	0.192***	-0.00914
	(0.0179)	(0.0291)	(0.0133)
RECOM	0.000725***	-0.00134***	0.000520***
	(6.45e-05)	(0.000153)	(5.44e-05)
GEXPER	-2.75e-05*	8.83e-06	-2.40e-05
	(1.59e-05)	(4.19e-05)	(1.46e-05)
FEXPER	-0.000103***	0.000233***	-8.17e-05***
	(1.92e-05)	(5.11e-05)	(1.88e-05)
FCAGE	2.75e-05***	-4.25e-05***	1.30e-05***
	(1.84e-06)	(3.83e-06)	(1.28e-06)
BRSIZE	-0.000235**	0.000695**	6.62e-05
	(0.000115)	(0.000300)	(0.000100)
INFOINT	-0.000133***	0.000272***	-0.000119***
	(1.19e-05)	(3.31e-05)	(8.88e-06)
INDCONC	0.000591	-0.000159	0.00109***
	(0.000366)	(0.000993)	(0.000299)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
Constant	0.00788***	-0.0157***	0.00782***
	(0.00176)	(0.00283)	(0.00249)

Observations	95,009	31,823	63,186
R-squared	0.143	0.126	0.084

*Firm-clustered, robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 6

Analyst affiliation and guided forecasts

This table presents selected results from the following probit regression:
$Guided\ forecasts = \beta_{0i} + \sum \beta_{mi} Dummy\ for\ affiliation_{mi} * ZSCR + \sum \beta_{ni} Control_{ni} + \varepsilon_i$
GUIDED is a dummy, receiving the value of one if the forecast is lower than actual earnings by an amount smaller than 10 cent of a dollar and zero otherwise. *DU*, *EU* and *EDU*, are affiliation dummies, respectively receive the value of one if the analyst is affiliated with one of the followed firm's debt underwriters, equity underwriters, or underwriters that participate in both debt and equity issues. *ZSCR* is Atman's Z-score. *DU#ZSCR* is the interaction term between *DU* and *ZSCR*. *EU#ZSCR* is the interaction term between *EU* and *ZSCR*. *EDU#ZSCR* is the interaction term between *EDU* and *ZSCR*. *GEXPER* is general experience. *FCAGE* is the number of days from forecast announcement to announcement of actual earnings. *TOPBANK* is the bank's size. *INFOINT* is the followed firm's information intensity. *INDCONC* is the analyst's industry concentration. *AT* is logarithm of the followed firm's total assets.

VARIABLES	(1) GUIDED	(2) GUIDED	(3) GUIDED
DU	0.0818***	-0.117**	0.559***
	(0.0235)	(0.0595)	(0.151)
EU	-0.135***	-0.149***	-0.552***
	(0.0210)	(0.0268)	(0.0917)
EDU	-0.136***	-0.241***	0.292
	(0.0379)	(0.0826)	(0.198)
ZSCR		2.84e-05*	
		(1.54e-05)	
AT			0.0207**
			(0.00980)
DU#ZSCR		0.0770***	
		(0.0174)	
EU#ZSCR		-0.000567	
		(0.00182)	
EDU#ZSCR		0.0945***	
		(0.0348)	
DU#AT			-0.0488***
			(0.0154)
EU#AT			0.0592***
			(0.0125)
EDU#AT			-0.0460**
			(0.0213)
RECOM	-0.0445***	-0.0448***	-0.0441***
	(0.00473)	(0.00537)	(0.00465)
GEXPER	0.00591***	0.00581***	0.00634***
	(0.00134)	(0.00161)	(0.00134)
FEXPER	0.00933***	0.0112***	0.00787***
	(0.00224)	(0.00262)	(0.00217)
INFOINT	0.0106***	0.0115***	0.00864***
	(0.00125)	(0.00145)	(0.00154)
INDCONC	-0.0630*	-0.0676*	-0.0597*
	(0.0351)	(0.0409)	(0.0350)
FCAGE	-0.00178***	-0.00198***	-0.00172***
	(0.000117)	(0.000132)	(0.000118)

TOPBANK	0.00974	0.0214**	-0.000351
	(0.00909)	(0.0103)	(0.00929)
Industry dummies	Yes	Yes	-0.272
Year dummies	Yes	Yes	Yes
Constant	-0.524**	-0.472**	-0.672***
	(0.224)	(0.211)	(0.231)
Observations	229,071	175,774	229,032

*Firm-clustered, robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*