Career Concerns of Banking Analysts

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ABSTRACT

We study how career concerns influence banking analysts' forecasts. Banking analysts' first (last) earnings forecast of the year is relatively more optimistic (pessimistic) for a bank that could be their future employer. This pattern is not observed when the same analysts forecast earnings of banks unlikely to be their future employer. We use the Global Settlement as an exogenous shock on career concerns and show that this forecast pattern is more pronounced after the Settlement. Moreover, we find evidence that more biased analysts in their forecasts of potential future employers are more likely to move to a higher reputation bank.

JEL Classification: G14, G24, G28, G32

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1. Introduction

Sell-side analysts are important information intermediaries in capital markets and as a result their research has been under scrutiny. While a large number of studies document that analyst coverage and forecasts have economic consequences (Bailey et al., 2003; Jackson, 2005), an equally large number of studies document that analyst forecasts are influenced by conflicts of interest (Beyer and Guttman, 2011; Cowen et al., 2006; Hong and Kubik, 2003; Jackson, 2005; Lim, 2001; Richardson et al., 2004; Schipper, 1991). In this paper we concentrate on the banking industry and investigate whether analyst forecasts are biased because of career concerns.

Past studies have documented that analyst forecasts can be biased because of underwriting activities in the investment banking business, pressure to generate trading commissions, and career concerns (Hunton and McEwen, 1997; Lin and McNichols, 1998; Michaely and Womack, 1999; Dugar and Nathan, 1995; Dechow et al., 2000; O'Brien et al., 2005; Hong and Kubik, 2003). In terms of career concerns, past studies have documented that more optimistic analysts tend to experience favorable job separations (Hong and Kubik, 2003) and younger analysts tend to herd more (Hong et al., 2000). In these studies, the underlying source of career concerns is pressure from investment banking and/or brokerage business to please companies or buy-side portfolio managers respectively.

In this paper, we concentrate on a different source of conflicts of interest. Banking analysts issue forecasts for companies that constitute a large part of their outside opportunities in terms of employment. These analysts view the banks that they issue forecasts for as potential sources of employment, thereby increasing their incentives to satisfy those clients. This is independent of incentives to generate investment banking business or trading commissions, which exist for all companies they cover.

In order to examine whether this pressure to satisfy future potential employers is influencing analyst forecasts, we examine the pattern in the bias of their forecasts. In our research design we hold the analyst constant by requiring that the same analyst is forecasting earnings for companies with sell-side equity departments ('employers') and for companies with no sell-side equity departments ('non-employers'). We then show that banking analysts issue forecasts that are relatively more optimistic for employers in the beginning of the year. At the end of the year the opposite is true; banking analysts issue forecasts that are relatively more pessimistic for employers. Therefore, our research design is similar to a differences-in-difference specification where we observe, for the same set of analysts, the forecasting pattern early and late in the year and we compare this pattern for employers and non-employers. We limit our sample to those analysts who are not employed by the top investment banks and therefore could have relatively greater career concerns. Analysts that are already working for bulge investment banks have greater career opportunities and less incentive to move as they already work at the most reputable banks. Therefore, we treat analysts working at the top banks as a control group that allow us to scale our dependent variable of forecast bias. We report results using both this relative bias variable and an absolute bias variable relative to the stock price of the firm. We find similar results across both measures.

To further identify the effect of career concerns from forecasting earnings of a potential future employer we exploit an exogenous shock to future career opportunities. The Global Settlement of 2003 decreased significantly the budgets for sell-side research and as a result directly impacted the outside opportunities for sell-side analysts (Cowen et al., 2006). This could lead to exacerbation of career concerns and as a result a more pronounced walk-down to beatable earnings for employers. On the other hand, after the Global Settlement, the analysts could be more reluctant to bias their forecasts because that might anger other constituents that consume their forecasts, raising the probability of dismissal. The probability of a promotion at another firm might not look as attractive if analysts are more worried about just keeping their jobs after the settlement. We find that after the Global Settlement the transition from optimistic to pessimistic forecasts closer to the year-end is stronger. These findings are consistent with banking analysts understanding that their forecasts could impact future career opportunities and as a result provide a walk-down to beatable earnings.

We analyze future job separations to understand whether analysts benefit from such forecasting activity. We find that banking analysts who are pessimistic at their latest forecast are more likely to experience favorable job separations and move to a higher status brokerage house. This result is present only for analysts that exhibit this behavior towards employers, again consistent with analysts strategically biasing their forecasts because of career concerns.

Our identification strategy aims to mitigate the likelihood that other sources of bias, unrelated to a revolving door story, might cause our results. We do so by differentiating both across types of firms being forecasted (i.e. a bank with or without a research department) as well as across analysts (i.e. employed by a top-bank versus a non-top bank). We show that a walk-down to beatable earnings and upward job mobility is more pronounced when an analyst works for a non-top bank and forecasts earnings of a bank with a research department. It is hard to reconcile these findings with biases due to incentives to generate investment banking business or trading commissions, which should be present in both types of forecasted firms or analysts. For example, bias arising from incentives to generate investment banking business should be strong for banks with or without research departments and it should be less pronounced after the Global Settlement. Similarly, incentives to generate trading commissions should be as strong for analysts working at top banks and when forecasting earnings for banks without research departments. Of course, if for example, investment banking business or trading commissions are significantly higher for banks with research departments and analysts in non-top banks have stronger incentives to bias their forecasts to generate investment banking business or trading commissions that could explain our results. However, in our matched sample, banks with and without research departments exhibit very similar market capitalization, valuation ratios, analyst following, share turnover, and risk; all variables that could be related to investment banking or trading commission sources of bias. Moreover, reduced competition, due to brokerage house closures, following the Global Settlement could explain our results (Hong and Kacperczyk, 2010). We address this concern by examining whether the pattern we document holds for firms where analyst coverage did not decrease after the Global Settlement and therefore the competition effect is not at play. We find similar results for this subsample.

Our results contribute to a body of literature that investigates the sources of bias in analyst forecasts (Cowen et al., 2006). We complement this line of research by documenting a different source of conflict of interest. Effectively the conflict we document here relates to the 'revolving-door' phenomenon, which has been investigated in relation to audit partners (Menon and Williams, 2004; Geiger et al., 2005), SEC lawyers (deHaan et al., 2015), and credit rating analysts (Cornaggia et al., 2016). We show that this effect generalizes in settings outside auditing and, consistent with Cornaggia et al. (2016), affects information intermediaries more broadly.

The results in this paper contribute also to a literature that seeks to understand whether financial institutions are more opaque and therefore characterized by higher information asymmetry and more information risk (Morgan, 2002; Flannery et al., 2004). Given that sell-side analyst activity improves the information efficiency of capital markets, our results suggest that the career concerns banking analysts are facing could contribute to a poorer information environment for financial institutions.

The paper proceeds as follows. In Section 2, we review the related literature and form the hypotheses of this study. Section 3 describes the data and research design. Section 4 details the descriptive statistics and we present the results in Section 5. We conclude in Section 6.

2. Past literature and hypotheses development

If analyst forecasts are formed objectively and errors arise from unforeseen events, there should not be any trend over time in the distribution of earnings surprises. Similarly, if analyst forecasts are unbiased, there is no reason to think that the distribution of surprises should differ across different types of firms or industries. However, the existence of an optimistic bias in analyst forecasts is well documented in many studies (Fried and Givoly, 1982; Klein, 1990; Brown et al., 1987; O'Brien, 1988; Affleck-Graves et al., 1990).

The evidence of forecast bias has led to many studies proposing and testing incentive-based explanations. For example, analysts have incentives to maximize the trading volume in the stock they cover to increase trading commissions earned (Jackson, 2005; Cowen et al., 2006; Beyer and Guttman, 2011). Similarly, evidence suggests that analysts from brokerage houses that have underwriting relationships with a company tend to issue more optimistic forecasts (but not less accurate) than unaffiliated analysts (Hunton and McEwen, 1997; Lin and McNichols, 1998; Michaely and Womack, 1999; Dugar and Nathan, 1995; Dechow et al., 2000; and O'Brien et al., 2005).

Similarly, they are likely to take into account the impact their forecasts may have on their relationship with management (to increase investment banking business or to curry favor with management to obtain and maintain access to private information) by issuing favorable (Schipper, 1991; Lim, 2001) or beatable (Richardson et al., 2004; Bartov et al., 2002) earnings forecasts. More recent literature examines the inter-temporal pattern in forecast bias and finds a trend from optimism to pessimism within both quarterly and annual fiscal periods (Cowen et al., 2006; Richardson et al., 2004; Ke and Yu, 2006). Cowen et al. (2006) document for a sample of forecasts issued from January 1996 to December 2002, 180 day+ forecasts are positively biased, 91 to 180-day forecasts are unbiased, and 0 to 90-day forecasts are negatively biased. Similarly, Richardson et al. (2004) document the optimistic to pessimistic pattern (or 'walk-down') of both annual and quarterly forecasts and Ke and Yu (2006) find that annual forecasts are on average optimistic and quarterly are pessimistic. The walk down of expectations is found to benefit both analysts and firms subject to the forecast. Ke and Yu (2006) finds that analysts with an optimistic to pessimistic pattern of forecasts are less likely to be fired by their employers, relative to analysts not providing such a pattern. While Bartov et al. (2002) finds that firms who beat their earnings expectations enjoy a higher overall return than firms who fail to do so, despite the expense of a drop in the share price following the walk-down in expectations.

Unlike other analysts, banking analysts issue forecasts for companies that constitute a large part of their outside opportunities in terms of employment. These analysts may view the banks with sell-side equity departments that they issue forecasts for as potential sources of employment ('employers'), as opposed to forecasting companies with no sell side equity department ('non-employers') thereby increasing their incentives to satisfy the former. This is independent of incentives to generate investment banking business or trading commissions for their own employers that should exist when making forecasts for all companies they cover. If this is true then analysts who forecasts both employers and non-employers will have stronger career incentives (resulting in a greater need to curry favor with the managers from these potential employers), and therefore are more likely to bias their forecasts for the employers relative to the non-employers they cover. This leads us to our first hypothesis:

Hypothesis 1. The change in the bias of the forecasts over time from optimistic to pessimistic is greater when forecasting earnings of employers relative to non-employers.

To further explore the effect of analyst career concerns we employ the Global Settlement of 2003 as an exogenous shock. This regulation changed the way brokerage firms profit from analyst activity and thereby increased the level of competition in the sell-side analyst labor market. The Global Settlement was initiated to curb the biased research produced by brokerage houses and resulted in ten of the largest banks paying nearly $1.4 billion in fines. Among other provisions, the Global Settlement created a "Chinese Wall" between the research divisions and the investment banking divisions of brokerage houses. Importantly, these provisions prohibited the explicit cross-subsidization of research activities from underwriting activities, drastically altering the demand for sell-side analysts at investment banks.

This regulatory shock changed the labor market landscape. As Cowen et al. (2006) note, investment banks decreased their spending on equity research by more than 40% as compared to 2000 levels, which reduced analyst head count on average by 15% to 20% and cut analysts' compensation by a third or more. This significant increase in competition in the sell-side analyst labor market allows us to test the effect of future career concerns on forecast bias. The sign of this effect, increasing or reducing analyst bias, however is unclear. It could be the case that, following the Global Settlement, forecast bias decreases as analysts switch their focus, to one of keeping their current job rather than striving for promotion at another investment bank. Under this scenario, analysts may take fewer risks and be reluctant to issue significantly biased forecasts just in case it potentially displeases their clients and thereby increases the likelihood of dismissal.[1] An alternative scenario, is that following the Global Settlement, analyst career concerns may have been exacerbated and consequently analysts may have stronger incentives to walk down their forecasts to beatable earnings. This could be particularly true for our sample as the Global Settlement focused much more on the top banks

[1] We would like to thank our anonymous reviewer for highlighting this possible scenario.

(which were the subject of the Settlement) than medium and low tier banks. Ultimately the effect of the Global Settlement on analyst career concerns is an empirical question and leads us to our second hypothesis:

Hypothesis 2. The bias of the forecasts over time from optimistic to pessimistic due to career concerns changes following the Global Settlement.

Prior research also investigates whether forecast bias is associated with an analyst's career and subsequent advancement (Ke and Yu, 2006; Hong and Kubik, 2003; Lourie, 2014). Ke and Yu (2006) find that analysts who issue initial optimistic forecasts followed by pessimistic forecasts, just before the earnings announcement, are less likely to be fired by their employers. Hong and Kubik (2003) find that the association between accuracy and turnover varies with the analysts' level of optimism and affiliation status. In particular, controlling for accuracy, analysts who issue optimistic earnings forecasts relative to the consensus are more likely to experience favorable job separations and thereby move up the brokerage house hierarchy. Furthermore, the turnover decisions of affiliated analysts depends less on accuracy and more on optimism than those of unaffiliated analysts.

The revolving-door literature also provides evidence that career incentives may cause individuals to lose objectivity in their assessment of potential future employers. Lourie (2014) investigates the forecast bias of analysts who leave the profession and are subsequently hired by firms the analyst had previously covered. He finds that analysts prior to their new employment provide more optimistic recommendations and higher target prices, for the firms that subsequently hire them, although he finds no systematic forecast earnings bias for these firms. Cornaggia et al. (2016), investigates the revolving door phenomenon, in relation to credit rating analysts and finds that transitioning credit rating analysts become more favorable to their future employers prior to their transition. They conclude that these conflicts of interest at the analyst level distort credit ratings.

If analysts are biasing employers' forecasts because of future career incentives, then following the findings of Hong and Kubik (2003) we would expect such analysts to benefit from this activity and thereby experience more favorable job separations. This leads us to our third hypothesis:

Hypothesis 3. Analysts who provide more biased earnings forecasts for employers are more likely to experience favorable job separations.

3. Data and research design

3.1. Sample of analysts

We obtain data on all individual analysts' forecasts of annual earnings per share from the Institutional Brokers Estimate System (I/B/E/S) Detail File. For a sample period from 1999 to 2006, we identify all banks with investment arms. This identification starts with the SIC codes 60-62,[2] and the Bloomberg categorization of investment services, but in order to be confident in our identification process we also use the information disclosed in the banks' annual reports and websites to validate our identification. We do not include observations post 2006 due to the financial crisis, although we find that our results are not sensitive to extending the sample period to 2012.[3] From this sample we extract sell-side analysts that follow both firms with sell-side equity departments (for convenience we term these 'employers') and firms with no sell-side equity departments (again for convenience we term these 'non-employers'). Requiring that the same analysts make forecasts across both groups mitigates the probability that differences in the results are driven by differences in the types of analysts making the forecasts. Moreover, since we find that well over 90% of our investment bank sample are within the S&P 500, we also limit our analysis to S&P500 firms

[2] We do not however classify those firms with a SIC code of 6099 (commercial banks) and 6111 (credit and debit card issuer) as employers.
[3] The global financial crisis is commonly believed to have begun in July 2007, and given we are investigating both the first and last analysts forecasts we limit our sample period to the end of 2006.

only; this again mitigates the probability that differences in the results are driven by differences in the types of firms being forecasted. However, if we relax both of these requirements the results continue to hold.

Similar to prior literature (Hong et al., 2000; Richardson et al., 2004; Kim et al., 2011) we consider only the last and first forecast for each analyst-firm pair during the twelve months of the annual earnings release date reported by I/B/E/S period. We exclude observations with forecast horizons shorter than one month and longer than one year (Clement and Tse, 2005) and also exclude those observations with negative price-to-book ratios and stock prices less than or equal to one dollar, thereby ensuring that illiquid stocks do not influence our results.

To obtain a benchmark of forecast bias when career concerns are weaker that allows us to better identify the effect of career concerns on forecasts, we use top brokerage house analysts as a control group. Given our focus is on analysts' career concerns we exclude from our sample all analysts employed by the top brokerage houses[4] (defined in the next section 3.2.) because these analysts will have lower career concerns as they already work for a top brokerage house and are less likely to bias their forecast to satisfy potential future employers. If this assumption is incorrect and analysts at top investment banks have equally strong incentives to walk-down expectations this would bias our analysis against finding any results. Thus, our sample only captures those analysts who have stronger incentives to satisfy potential future employees and move up the brokerage house echelons. Our sample contains 228 individual analysts who issue forecasts in the same year for both employers and non-employers. The additional firm-specific data is obtained from Compustat.

3.2. Measuring brokerage house status

To classify the brokerage houses into different status groups, consistent with Hong and Kubik

[4] Although we exclude the analysts from the top brokerage houses from the sample we do use their forecasts to determine the relative forecast bias.

(2003), we measure the status of the brokerage house based on the number of analysts from each brokerage house who issue forecast reports. Unfortunately, we were unable to use an external ranking system, such as the one published by *Institutional Investor*, as we could not identify the exact name of the brokerage house that the analysts worked for (since I/B/E/S simply provides a code for each brokerage house not the name).[5] However, Hong and Kubik (2003) find that this alternative measure of brokerage house status based on the size of a brokerage house is highly correlated to the *Institutional Investor* ranking system. To replicate Hong and Kubik (2003) proportions of brokerage houses identified as top, medium and low status we identify a high-status house as a brokerage house in the top 3% in terms of size each year. Low-status is any brokerage house size below the average house size each year and the remaining are identified as middle-status houses. Consistent with Hong and Kubik (2003) who report that approximately 29% of their sample analysts are identified as employed by high status brokerage houses, we find approximately 31.5% of our sample analysts are identified as being employed by high-status houses. Moreover, we find that approximately 22.2% and 46.3% of analysts worked in low-status houses and median-status houses respectively, which again is consistent with the statistics reported by Hong and Kubik (2003).[6]

3.3. Research design: Measuring forecast bias

To measure analyst bias, we adopt two approaches used in prior literature (Jacob et al., 1999; Clement, 1999; Hong and Kubik, 2003; Cowen et al., 2006; Walther and Willis, 2013). Our first measure compares the optimism of a given analyst's forecast for a particular firm and time period to the mean optimism of all analysts employed by the top brokerage houses who make forecasts for the same firm and time period within a comparable forecast horizon. This requires us to exclude those firms followed by fewer than three analysts as our forecast bias

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[5] We were unable to obtain the Broker Transaction file which would enable us to identify the brokerage houses' name.

[6] We investigated alternative cut-off points, however, our results are not sensitive to either a 1% increase or decrease to this identification metric.

measure requires intra firm-year variation (Clement and Tse, 2003; Kerl and Ohlert, 2015). Note, this constraint reduces the number of firm-year observations but not the number of individual analysts. This relative performance metric controls for any company-specific or time-specific factors that affect forecast optimism. We define forecast bias of analyst *i* for firm *j* in year *t* (FB_{ijt}) as the signed difference between the forecast and the actual earnings per share (EPS). Where:

$$FB_{ijt} = Forecast\ EPS_{ijt} - Actual\ EPS_{ijt}$$

and to control for the firm-year effects the demeaned version of FB_{ijt} is[7]:

$$Rel\_DFB_{ijt} = \frac{\left[FB_{ijt} - Avg(TopFB_{jt})\right]}{\left|Avg\left(TopFB_{jt}\right)\right|}$$

where $Avg(TopFB_{jt})$ is the average forecast bias across all analysts working at top brokerage houses, as defined above, for firm *j* in year *t*.

Our second measure consistent with Walther and Willis (2013) is an absolute forecast bias based on the signed forecast error as a percentage of share price:

$$Abs\_DFB_{ijt} = \left[\frac{FB_{ijt}}{P_{jt}}\right] * 100$$

where P_{jt} is the share price from firm *j* for year *t* issued 10 trading days before the forecast release date.

If either Rel_DFB_{ijt} or Abs_DFB_{ijt} is positive, then the analyst forecast is optimistically biased (positively biased) whereas if it is negative then the analyst forecast is pessimistically biased (negatively biased). We calculate two Rel_DFB_{ijt} (and two Abs_DFB_{ijt}), one for the first forecast and one for last forecast analyst *i* makes for firm *j* in year *t*.

3.4. Modeling forecast bias between employers and non-employers

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[7] We deflate the variable with the absolute mean of the top analysts forecast error for each firm-year since Clement (1999) shows that this procedure reduces heteroscedasticity.

To test hypothesis 1, that employer forecasts are relatively more biased than non-employer forecasts, we estimate the following cross-sectional regression that includes an indicator variable *EMPLOYER* that equals one if the analyst is forecasting earnings of a potential future employer and zero otherwise:

$$Rel\_DFB_{ijt}\ (or\ Abs\_DFB_{ijt}) = \beta_1 EMPLOYER + \beta_2 Earn\_Std_{jt} + \beta_3 Ln(MV_{jt}) + \beta_4 Ln(BTM_{jt}) + \beta_5 Ln(Follow_{jt}) + \beta_6 F\_Horizon_{ijt} + \beta_7 dayElap_{ijt} + \beta_8 fr_{ijt} + \beta_9 Firm\_Exp_{ijt} + \beta_{10} Gen\_Exp_{ijt} + \beta_{11} Num\_Co_{ijt} + \beta_{12} Num\_Ind_{ijt} + \beta_{13} Num\_Ana_{ijt} + \beta_{14} Year\ F.E + \beta_{15} Analysts\ F.E + \varepsilon_{ijt} \tag{1}$$

We estimate this model for both the first forecast and last forecast the analyst makes for firm *j* at time *t*. If employer forecasts are relatively more biased than non-employer forecasts then we would expect β_1 to be significantly different from zero. Under hypothesis 1 we expect β_1 to be positive and significant for the first forecast and negative and significant for the last forecast. Equation (1) includes a number of control variables proposed in the prior literature that are also likely to be related to forecast bias. The first controls for the predictability of earnings, Das et al. (1998) argues that when earnings are less predictable, analysts have stronger incentives to issue optimistic forecasts to facilitate information acquisition from management. We use earnings dispersion (*Earn_Std*) to measure earnings uncertainty (Barron et al., 1998; Gu and Wu, 2003). Similar to other studies (Gu and Wu, 2003, Clement, 1999; Clement and Tse, 2005, Bradshaw, 2011) we also control for firm size (*Ln(MV)*), book to market (*Ln(BTM)*), and analyst following (*Ln(Follow)*); along with a number of forecast specific control variables: forecast horizon (*F_Horizon*), days elapsed (*dayElap*) and forecast frequency (*fr*). Consistent with Clement (1999) and Hong and Kubik (2003) we also control for analyst specific experience (*Firm_Exp* - the number of years the analysts has forecasted firm *j*); general experience (*Gen_Exp* - number of years the analysts had been forecasting), along with proxies for analysts' portfolio complexity - the number of firms (*Num_Co*) and industries (*Num_Ind*) the analyst follows during time *t*; also we include the brokerage house size (*Num_Ana*) as well as year fixed effects (*Year F.E.*) and analysts fixed effects (*Analysts F.E.)*. When the dependent variable is *Rel_DFB,* the analyst or forecast-level independent variables are adjusted by their related firm-year means to properly control for firm-year effects (Clement, 1999). To mitigate the influence of outliers and improve the explanatory power of the *Rel_DFB* model, which tends to be low because firm-specific drivers of forecast error are removed from the analyst forecast (Clement, 1999; Cowen et al, 2006) we winsorize at the bottom and top 5%. All our results are qualitatively unchanged if we winsorize at the 1% level with the only difference being that the explanatory power of the model decreases. The appendix provides details on the measurement of each of these variables. Robust standard errors are clustered at the analyst level.

To examine the effects of the Global Settlement and test hypothesis 2 we modify equation (1) by including an interaction term *EMPLOYER*POST*, where *POST* is an indicator variable which takes the value of one if the forecast is after the Global Settlement e.g. 2004-2006; and zero if the forecast is before the settlement e.g. 1999-2002. We exclude the year the Global Settlement was implemented thereby removing any possibility of differing effects in that year due to different timings of the analyst forecasts. Under hypothesis 2, if employer forecasts are relatively more biased than non-employers forecasts following the Global Settlement then we would expect the coefficient on the interaction term to be significantly different from zero. Specifically, we expect the coefficient to be positive and significant for the first forecast and negative and significant for the last forecast.

3.5. Modeling forecast bias and job separation

3.5.1. The sample

To investigate the impact of forecast bias on job separation we obtain a sample of all analysts who moved brokerage houses during 1999-2006. Consistent, with our prior analysis we exclude those analysts from top brokerage houses. This results in a sample of 468 unique analysts from medium and small brokerage houses who moved employers. Unlike our prior sample we do not need to restrict this sample to those analysts that forecast both employers and non-employers, thus this movement sample also includes analysts who may only forecast employers or analysts who may only forecast non-employers.

3.5.2. Modeling forecast bias and job separation

We estimate the following ordinal logit specification to test hypothesis 3:

$$Move\_status_{t+1} = \beta_1\, BIAS_{ijt} + \beta_2 EMPLOYER + \beta_3\, BIAS_{ijt} * EMPLOYER + \beta_4 Gen\_Exp_{it} + \beta_5 Num\_Co_{it} + \beta_6 Accuracy_{it} + \beta_7 Status\ F.E. + \beta_8 Year\ F.E + \varepsilon_{ijt} \tag{2}$$

Move_status takes a discrete value of -1, 0, 1, or 2, depending on whether the analyst has moved that year to a higher or lower status house and the size of the jump made. For example, analyst *i,* who moves up to a higher status brokerage house (i.e. is promoted) in year *t,* is given the value of 1 if it involves one movement up the hierarchy of brokerage house status (i.e. low status to middle status or middle status to high status) and the value of 2 if the move up represents a move of two hierarches (i.e. low status to high status). Analyst *i,* who moves down to a lower status brokerage house in year *t,* is given the value of -1 if it involves one movement down the hierarchy of brokerage house status (i.e. middle status to low status). Because we limit our sample to those analysts moving from medium-status and low-status brokerage houses the maximum drop in hierarchy possible is -1 (medium to low). *Move_status* equals 0 if analyst *i* moves within the same hierarchy status. Consistent with Hong and Kubik (2003) we do not classify a status movement for the analyst if it is only the brokerage house that changes status during the year since the analyst has not experienced a job separation and we also exclude brokerage houses which merged during the year.

We follow a similar methodology to that of Hong and Kubik (2003) and measure a relative forecast bias for each firm the analyst forecasts in each year (*Rel_DFB*) (i.e. relative to the average bias of analysts from top brokerage houses) and then average across the stocks that the analysts from top brokerage houses covers. This produces a bias measure for analyst *i* in year *t*. However, this relative bias measure will be noisy for analysts that only follow a few firms in a year. Therefore, consistent with Hong and Kubik (2003) we create the measure *Rel_BIAS* that is the average of the analyst's forecast biases in year *t* and the two previous years. As noted by Hong and Kubik (2003) such a long averaging period increases the signal-to-noise ratio of the measure. For those analysts that forecasted both employers and non-employers we measure separate *Rel_BIAS* for their employers' forecasts and their non-employer forecasts.[8] Whereas those analysts that covered only non-employers, the *Rel_BIAS* measure is based on all firms covered.[9] We also construct *Abs_BIAS* in a similar manner.

In addition, we control for general experience in terms of number of years the analyst has been forecasting for (*Gen_Exp*), the number of firms the analysts follows during the three year window (*Num_Co*) and whether the analysts is in the top decile of forecast accuracy during the same period (*Accuracy*). Additionally, we also include indicator variables for the status of the brokerage house the analyst currently works for (*Status F.E.)*, as well as year fixed effects (*Year F.E.)*.

We estimate our model for both the first and last forecast the analyst makes for firms *j* at time *t*. If the forecast bias for employers is more important for job separation relative to a non-employers forecast then we would expect β_3 to be significantly different from zero.

4. Descriptive statistics

[8] The results are not sensitive to excluding the non-employer forecasts for those analysts forecasting both employer and non-employer.

[9] Since we are unable to identify the brokerage house name that an analyst works for (as we do not have access to Broker Transaction file) we are unable to directly link an analyst who moved to a particular investment bank that she had previously covered. Given we argue that biased forecasts help the analysts build relationships with prospective employers then a banking analysts will always provide more biased forecast irrespective of whether they ultimately work for a specific investment bank they cover.

We report descriptive statistics in Table 1. Panel A shows the distributions of the forecast bias (*Rel_DFB* and *Abs_DFB*) for the full sample, employer sample and non-employer sample. Preliminary investigation of the differences between the employer forecast bias and non-employer forecast bias reveals that for relative bias (*Rel_DFB*), employer first forecast is significantly more optimistic than non-employer, and the employer last forecast is significantly more pessimistic than non-employer. The absolute bias (*Abs_DFB*) provides a consistent picture with respect to the first forecast but a different one with respect to the last forecast as we find this forecast is significantly more optimistic for employer versus non-employer. Panel B shows the distribution of the firm and analyst characteristics for the relative and absolute bias analysis, based on the first forecast sample. The distributions are similar to prior studies (Clement and Tse, 2005).

We report correlations among the analysts' forecast bias and analyst forecast and firm characteristics in Panel C. Below (above) the diagonal we report correlations for the last (first) forecast sample. *EMPLOYER* is positive and significantly correlated to bias for the first forecast and negatively but not significantly correlated to bias for the last forecast. *EMPLOYER* is also significantly correlated to a number of firm and standardized analyst characteristics, specifically a positive correlation is noted for firm size (*Ln(MV)*), book-to-market (*Ln(BTM)*), analysts following (*Ln(Follow)*) and number of industries followed (*Num_Ind*); a negative correlation is noted for earnings dispersion (*Earn_Std*), analysts general experience (*Gen_Exp*) and number of companies followed (*Num_Co*). Consistent with prior research we find the firm characteristics of earnings dispersion and analysts following to be significantly correlated to forecast bias. The correlations among forecast characteristics and forecast bias are not significant, except for forecast horizon and forecast revisions. All the analyst characteristics are significantly correlated with the first forecast bias, but not the last forecast bias.

5. Results

5.1. Forecast bias for employers versus non-employers

Table 2 Panel A presents estimates of equation (1) where the dependent variable is relative forecast bias (*Rel_DFB*) in columns (1) and (2) and absolute bias (*Abs_DFB*) in columns (3) and (4), for the analyst's first or last forecast. The coefficient on the indicator variable *EMPLOYER* for both the first forecast (column 1) and last forecast (column 2) is economically and statistically significant. The estimated coefficients on *EMPLOYER* reflect the incremental effect of optimism (pessimism) for a banking analyst that forecast a firm that is a potential employer in the future. Since the relative forecast bias is scaled by the average forecast bias of top analysts for this stock then the estimated coefficient can be interpreted in percentage terms of the average forecast bias of top analysts. Specifically, the coefficient on *EMPLOYER* for the first forecast is positive, indicating an optimistic forecast, and significant at the five percent level. The size of the *EMPLOYER* coefficient indicates that the average relative first forecast bias for employers is 9% more optimistic than for non-employers. In contrast, for the last forecast the coefficient on *EMPLOYER* is negative, indicating a pessimistic forecast, and is significant at the ten percent level. The size of the *EMPLOYER* coefficient indicates that the average relative last forecast bias for employers is 22.6% more pessimistic than for non-employers. These results provide support for hypothesis 1 that analysts are more biased with respect to employer forecasts than non-employer forecasts and that this bias follows an optimistic to pessimistic pattern. The alternative bias measure, *Abs_Bias* (column 3 and 4), provides a similar pattern to *Rel_Bias*. The first forecast bias for employers is 10.4% more optimistic and significant at the one percent level. Whilst the last forecast bias for employers is 17.9% more pessimistic and significant at the one percent level.

These findings are consistent with our argument that analysts who forecast earnings of both employers and non-employers will have stronger career incentives influencing their employer forecast. To rule out differences in task difficulty as an alternative explanation driving our results, in unreported results, we calculate two forecast accuracy measures. The first is a relative forecast accuracy measure, similar to Clement and Tse (2003), where analyst *i*'s forecast accuracy for firm *j* in year *t* is calculated as the maximum absolute forecast error for *top* analysts who follow firm *j* in year *t* minus the absolute forecast error of analyst *i* following firm *j* in year *t*, with this difference scaled by the range of absolute forecast errors for *top* analysts following firm *j* in year *t*. The exact calculation is:

$$Rel\_Forecast\ Accuracy_{\mathrm{ijt}}=\frac{AFEmax_{jt}\text{-}AFE_{ijt}}{AFEmax_{jt}\text{-}AFEmin_{jt}}$$

where:

$$AFE_{ijt}=\left|Forecast\ EPS_{ijt}\text{-}Actual\ EPS_{ijt}\right|$$

The second forecast accuracy measure is the absolute of *Abs_DFB* multiplied by minus one. The exact calculation is:

$$Forecast\ Accuracy_{ijt}=\text{-}1^{*}\ \left|Abs\_DFB^{*}100\right|$$

We find for the relative forecast accuracy measure the analysts' first employer forecast is significantly more accurate than their first non-employer forecast. In contrast, the last employer forecast is not significantly different to the last non-employer forecast. We find no significant difference between employer and non-employer for the absolute forecast accuracy. Thus, the optimism we observe for the first employer forecast cannot be attributed to the difficulty of the task (Bradshaw et al., 2016).

Among the standardized control variables in columns (1) and (2) the coefficient estimates for number of analysts covering the firm (*Ln(Follow)*) and forecast horizon (*F_Horizon*) are positive and significantly different from zero for both the first and last forecast analysis; consistent with Das et al. (1998) and Cowen et al. (2006). In addition, for the last forecast analysis, firm-size (*Ln(MV)*) and number of industries followed by the analyst (*Num_Ind*), is negative and significantly different from zero; consistent with Lim

(2001) and Clement (1999). While the estimated coefficients on days elapsed (*dayElap*) and analyst firm-specific experience (*Firm_Exp*) are significantly negative consistent with Cowen et al. (2006).

5.1.1. Only banks

We test the sensitivity of these results to alternative samples. First, from our main sample, we focus only on analysts with forecasts for banks with and without investment arms (mainly commercial banks therefore excluding other financial institutions). Certainly, these latter firms operate in a more similar setting and therefore have more similar risks and regulations compared to firms that provide non-financial services. The results are reported in Table 2 Panel B. We find, for both measures of bias, a similar pattern. *EMPLOYER* is positive and significant, with a coefficient of 0.09, for the first forecast when bias is *Rel_Bias* (Column 1) and negative and significant, with a coefficient of -0.236, for the last forecast (Column 2). For the *Abs_Bias* the *EMPLOYER* is positive and significant, with a coefficient of 0.107 (Colum 3) and negative and significant, with a coefficient of -0.272, for the last forecast (Column 4). The results are therefore not sensitive to this alternative sample.

However, given that the same analyst *i* might not forecast the same firm *j* in both the first and last forecast samples this raises an issue as to whether the coefficient on *EMPLOYER* might be different across first and last forecasts due to differences in the analyst-firm pair in the sample. To accommodate for this possibility, we pool the observations across both first and last forecast and include both analyst and firm fixed effects. We include an interaction term between *EMPLOYER* and *LAST* (which is an indicator variable equal to one for the last forecast, and zero for the first forecast). Our expectation is that the estimated coefficient on the interaction term will be negative and significant. We find strong evidence of this across both relative and absolute forecast bias. The results are reported in Table 2 Panel C.

5.1.2. Propensity score matching for employers and non-employers

We employ propensity score matching (PSM) and use a one-to-one matched pair design to identify for each analyst an employer and a non-employer. Our matching algorithm uses variables typically related to analyst forecast bias and firm-specific variables highlighted in the banking literature (Flannery et al., 2004; Anolli et al., 2014). Specifically, we match on a number of firm characteristics, book-to-market (*BTM*), size (*MV*), bid-ask spread (*Qspread*), stock turnover (*Turnover*), stock return volatility (*Total Risk*), insolvency risk (*Zscore*), number of analysts following the firm (*Follow*) and the firm-specific experience of the analyst following the firm (*Firm_Exp*). We also investigate the sensitivity of our results by creating a sub-sample of banks with and without equity departments. For this sub-sample we match on all variables noted above along with one additional firm-specific variable, return-on-assets (*ROA*). We include this additional variable given the accounting is similar for this sub-sample of firms, unlike for the full sample.

Table 3 (Panels A and B) reports the mean difference in covariate values for first and last forecast using the full sample and the banking sub-sample respectively. We assess the balance with reference to the bias reduction and t-test (columns 7 and 8). As Oakes and Kaufman (2006) suggests, after matching a standardized bias below 10% is desirable. Both panels reveal the impact of the matching process. In Panel A (full sample), other than *Firm_Exp* and *Qspread* (and *BTM* for first forecast sample), all covariate mean differences pre-matching are statistically significant (consistent with the correlations noted above) but after matching for the first forecast sample *BTM*, *Ln(Follow)* and *Turnover* differ significantly, and for the last forecast sample *Ln(Follow)* and *Total Risk* continue to differ, although all of the residual biases are below 10%. The bank sub-sample, Panel B, provides a similar picture with the majority of covariate means being significantly different pre-match (for both first and last forecast samples) and only a few covariate means differing significantly after the match. All the residual biases are below 10%, with the exception of *Ln(Follow)* and *Total Risk*.

Panel C reports the regression estimates using the matched samples for the full sample. Consistent with the prior results, using either *Rel_DFB* or *Abs_DFB* the variable of interest *EMPLOYER* is positive and significantly different for the first forecast at the 1% level (columns 1 and 3) and negative and significantly different for the second forecast at 5% level (columns 2 and 4). The size of the *EMPLOYER* coefficient (column (1)) indicates that the average relative first forecast bias for employers is 17.1% more optimistic than for non-employers and the last forecast bias is 78.8% more pessimistic than for non-employers (column (2)). Although this difference might seem too large, it is actually just four cents on a dollar. Similarly, for the banking sub-sample (Table 3, Panel D) the first forecast is positive and significant at the 1% (for both the relative and absolute forecast biases) and negative and significant at the 10% and 5% for the last relative forecast bias and absolute forecast bias respectively.

5.1.3. Non-linear controls

Lastly we test the sensitivity of the results by controlling for firm-specific and analyst's specific characteristics in non-parametric analysis. We recast all the control variables as indicator variables according to the quintile in which the value of the variables falls in. For example, instead of controlling for firm specific experience using a linear variable, we include four indicator variables as controls. In untabulated analysis, we find results consistent with the prior findings. Therefore, the results are not sensitive to this alternative specification.

5.1.4. Global Settlement

Table 4 presents the results of the impact of the Global Settlement on analyst career concerns and hence their forecast bias. Columns (1) and (2) report the results for the first and last forecasts respectively. We find the coefficient on the interaction term *EMPLOYER*POST* in column (1) to be positive and significant at the five percent level. This coefficient indicates that post Global Settlement analysts' first forecast for employers is 16.8% more optimistic than pre-settlement. In contrast, we find *EMPLOYER*POST* in column (2) to be negative and significant at the ten percent level, thus indicating that following the Global Settlement employers analysts' last forecast is 15.5% more pessimistic than pre-settlement. These findings are consistent with the Global Settlement increasing analyst incentives to bias their forecast and as a result provide an even steeper walk-down to beatable earnings.

However, reduced competition due to brokerage house closures following the Global Settlement, could explain our results (Hong and Kacperczyk, 2010). Therefore, we re-run the model, but exclude from the pre and post sample those firms who experienced a decrease in analysts' coverage following the Settlement. This new sample thereby reduces the possibility of the competition effect, noted by Hong and Kacperczyk (2010), influencing our results. The results are reported in Table 4 Panel B. We find similar results to those of the main sample (Table 4 Panel A).

Overall, the results suggest that the exacerbation of career concerns dominates any decrease in bias from potentially mitigating other conflicts of interest, consistent with the intention of the Settlement.

5.2. Forecast bias and job separation

Table 5, Panel A reports the percentage of analysts who work in high-status, medium-status and low-status brokerage houses. Consistent with Hong and Kubik (2003) we find approximately 31.5% of analysts worked in high-status brokerage houses each year. High-status brokerage houses in aggregate should not employ the majority of analysts; otherwise there would be little meaning to being considered working in a prestigious house. Table 5 Panel B reports the summary statistics of those analysts in the I/B/E/S database who leave their brokerage house but stay in the profession. About 6% of analysts change brokerage houses each year, during 1999-2006. Of these movers approximately 7% are analysts who cover employers (column 2). As a fraction of these movers, about 51% move up the hierarchy, about 30% move down the hierarchy and the remaining are lateral movers. These percentages are similar to the all analyst sample (Column 1).

Taking a slightly different look at these job separation patterns of analysts forecasting employers, on average during our period, approximately 16% of bank analysts moved from either high-status or low-status brokerage houses. The biggest movers are from mid-status houses where nearly 68% of bank analysts moved. Again, these percentages are similar to the all analyst sample.

Table 5 Panels C and D presents the results of estimations from the ordinal logit model, equation (2), for the various job separation measures involving movements along the brokerage house hierarchy. In Panel C, column (1), the *Rel_BIAS* relates to the first forecast bias, in column (3) it relates to the last forecast bias. We find the first forecast bias is not associated with job separation along the brokerage house hierarchy, and that analysts who forecast employers do not experience significantly different job separations from other analysts, since the coefficient on the interaction variable (*Rel_BIAS*EMPLOYER*) is not significantly different from zero. However, we find the last forecast bias (column 3) for analysts who forecast employers is associated with job separation along the brokerage hierarchy. Specifically, the coefficient on the interaction variable (*Rel_BIAS*EMPLOYER*) is negative, indicating that analysts who issue pessimistic forecasts for employers are relatively more likely to move up the brokerage hierarchy, compared to analysts who forecast non-employers. This result supports our hypothesis that analysts who bias their last employer forecasts downwards are more likely to experience favorable job separations. Panel D presents results using *Abs_BIAS* and again we find consistent results.

Given that interaction terms do not have a straightforward interpretation in nonlinear models as they do in linear models, we follow Ai and Norton (2003) and estimate marginal effects for different cells. Moreover, we report odds ratios for all estimated coefficients (columns 2 and 4). We note that no odds ratios can be calculated for the interaction effect but rather we report the ratio of the odds ratio for the interaction effect. Figure 1 shows the marginal effect for a unit change in bias for movements up or down the hierarchy based on whether the analyst makes forecasts for an employer or non-employer. For non-employers, bias does not affect movements. For non-employers, the marginal effect is 0.09% (z-stat=0.26) for downward movement and -0.25% (z-stat=-0.26) for upward movement as an analyst's bias increases. In contrast, for employers, the marginal effect is 1.51% (z-stat=-2.63) for downward movement and 7.28% (z-stat=2.07) for upward movement as an analyst's bias increases. Therefore, more biased analyst forecasts for employers are significantly more likely to be associated with promotions to higher reputation banks.

6. Conclusion

This paper investigates how career concerns of analysts that forecast the performance of potential future employers influence their forecasts. We find evidence of a walk-down to beatable earnings when forecasting earnings of future employers but not of companies that are unlikely to be future employers. Moreover, this pattern is more pronounced after the Global Settlement which likely exacerbated career concerns of analysts by limiting their outside opportunities. Consistent with career concerns about future employment biasing forecasts we find that bias in potential future employers' forecasts lead to favorable career outcomes. No such effect is found for bias in non-employer forecasts.

Our paper documents a source of conflict of interest for research analysts that is widely discussed in other settings, such as auditing but also more recently for other information intermediaries, such as credit rating analysts. Our findings open up opportunities for future research. Do investors recognize this source of bias when they incorporate analyst earnings forecasts in market prices? Do bias incentives from revolving doors generalize to investment recommendations? How bias in banking analyst forecasts has contributed to financial institution opacity?

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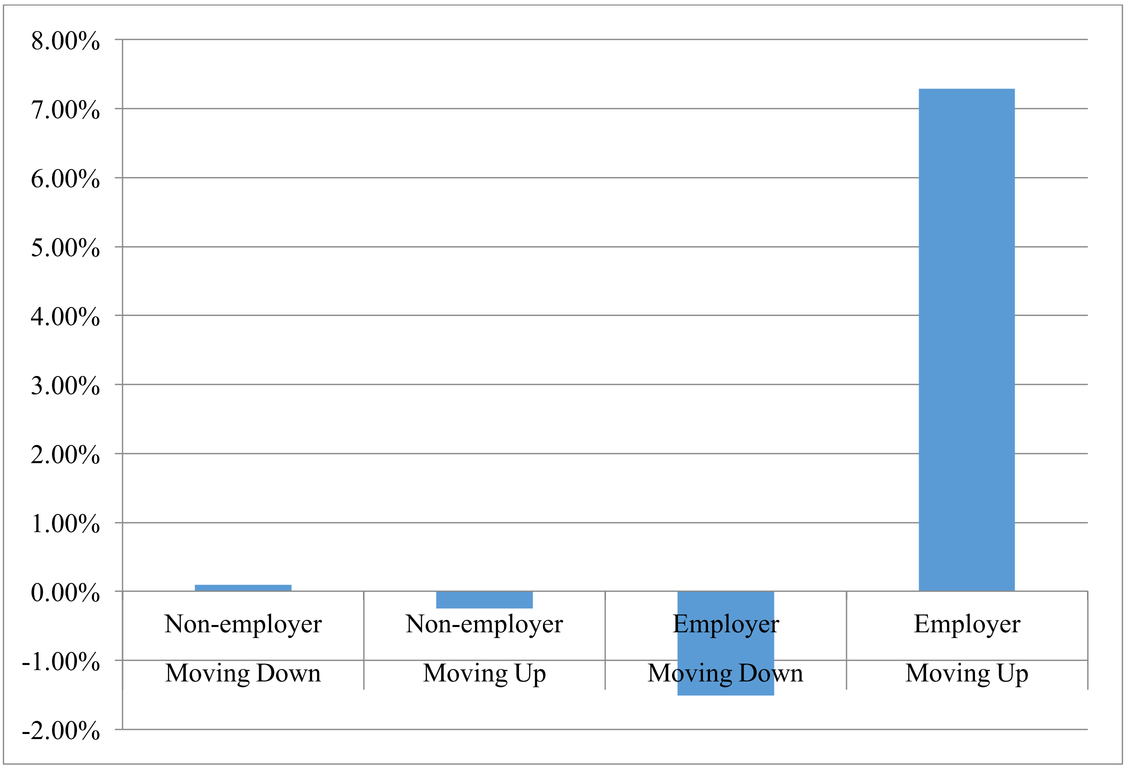
Figure 1

Figure 1 shows marginal effects of a unit change in bias for movement upwards or downwards in bank reputation calculated from a probit regression. It separates the effect based on whether analysts forecast earnings of employers or non-employers. Employer is any financial institution with a sell-side equity department where non-employer is any financial institution with no sell-side equity department.



Appendix: Variable Definitions

Name		Description
Rel_DFB_{ijt}	=	The difference between the forecast error for analyst *i* for firm *j* at time *t* and the average forecast error of analysts from top brokerage houses following firm *j* at time *t*, scaled by the mean absolute forecast error of top analysts for firm j at time *t*. Forecast error is estimated value for analyst *i* minus actual value of firm *j* at time *t*.
Abs_DFB_{ijt}		The absolute forecast bias for firm *j* at time *t* is based on the signed forecast error as a percentage of share price.
EMPLOYER	=	An indicator variable which takes the value of one if the forecast is for a company with a sell-side equity department (investment bank) and zero otherwise.
$Earn\_Std_{jt}$	=	Standard deviation of firm *j*'s prior 5 years earning in year *t.*
$Ln(MV_{jt})$	=	Natural log of the firm *j*'s market value at the end of year *t*.
$Ln(BTM_{jt})$	=	Natural log of the ratio of book value of equity to market value of firm *j* at the end of year *t.*
$Ln(Follow_{jt})$	=	Analysts following, measured as the natural log of analysts following firm *j* in year *t*.
$F\_Horizon_{ijt}$	=	The measure of the time from the forecast date to the end of the fiscal period, calculated as the forecast horizon (days from the forecast date to the fiscal year-end) for analyst *i* following firm *j* in year *t.* When we use (Rel_DFB_{ijt}) as dependent variable we rescale by subtracting the average forecast horizon for analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average forecast horizons for analysts from top brokerage houses following firm *j* in year *t*.
$dayElap_{ijt}$	=	The measure of the days elapsed since the last forecast by an analyst following firm *j* in year *t*. When we use (Rel_DFB_{ijt}) as dependent variable we rescale by calculating it as the days between analysts *i*'s forecast of firm *j*'s earnings in year *t* and the most recent preceding forecast of firm *j*'s earnings by analysts from top brokerage houses, minus the average number of days between two adjacent forecasts of firm *j*'s earnings by any two analysts in year *t*, with this difference scaled by the average days between two adjacent forecasts of firm *j*'s earnings in year *t*.
fr_{ijt}	=	The measure of analyst *i*'s forecast frequency for firm *j*, calculated as the number of firm *j* forecasts made by analyst *i* following firm *j* in year *t*. When we use (Rel_DFB_{ijt}) as dependent variable we rescale by subtracting the average number of firm *j* forecasts for analysts from top brokerage houses following firm *j* in year *t*, with this difference scaled by the average number of firm *j* forecasts issued by analysts from top brokerage houses following firm *j* in year *t*.
$Firm\_Exp_{ijt}$	=	The measure of analyst *i*'s firm-specific experience, calculated as the number of years of firm-specific experience for analyst *i* following firm *j* in year *t*. When we use (Rel_DFB_{ijt}) as dependent variable we rescale by subtracting the average number of years of firm-specific experience for analysts from top brokerage houses following firm *j* in year *i*, with this difference scaled by the average years of firm-specific experience for analysts from top brokerage houses following firm *j* in year *t*.
Gen_Exp_{ijt}	=	The measure of analyst *i*'s general experience, calculated as the number of years of experience for analyst *i* following firm *j* in year *t*. When we use (Rel_DFB_{ijt}) as dependent variable we rescale by subtracting the average number of years of experience for analysts from top brokerage houses following firm *j* in year *t*, with this difference scaled by the range of years of experience for analysts from top brokerage houses following firm *j* in year *t*.
Num_Co_{ijt}	=	The measure of the number of companies analyst *i* follows in year *t*, calculated as the number of companies followed by analyst *i* following firm *j* in year *t*. When we use (Rel_DFB_{ijt}) as dependent variable we rescale by subtracting the average number of companies followed by analysts from top brokerage houses who follow firm *j* in year *t*, with this difference scaled by the average number of companies followed by analysts from top brokerage houses following firm *j* in year *t*.
Num_Ind_{ijt}	=	The measure of number of industries analyst *i* follows in year *t*, calculated as the number of two-digit SICs followed by analyst *i*

		following firm j in year t. When we use (Rel_DFB_{ijt}) as dependent variable we rescale by subtracting the average number of two-digit SICs followed by analysts from top brokerage houses who follow firm j in year t, with this difference scaled by the average number of two-digit SICs followed by analysts from top brokerage houses following firm j in year t.
Num_Ana_{ijt}	=	The measure of the analyst's brokerage size, calculated as the number of analysts employed by the brokerage house employing analyst i following firm j in year t. When we use (Rel_DFB_{ijt}) as dependent variable we rescale by subtracting the average number of analysts employed by brokerage houses for analysts following firm j in year t, with this difference scaled by the average brokerage house size for analysts following firm j in year t.
$Qspread_{jt}$	=	The measure of a firms bid-ask spread is the average quoted spread of firm j in effect for transactions during the year ending at t.
$Turnover_{jt}$	=	The measure of a firm's turnover is the number of shares traded in firm j, divided by the number of shares outstanding at the end of the preceding year, time $t–1$.
$Totalrisk_{jt}$	=	The measure of total risk is estimated as the standard deviation of firm j of monthly returns (computed on a daily basis).
$zscore_{jt}$	=	A proxy for insolvency risk of firm j at the end of year t. A function of net income, total equity and standard deviation of ROA. See Anolli, et al., 2014, Boyd et al., 1993; Laeven and Levine, 2009. By construction higher values of the Z-score imply lower levels of risk.
ROA_{jt}	=	The measure of return on asset for firm j in year t is the net accounting income after taxes divided by total assets.

Table 1
Descriptive statistics on analyst and firm characteristics

This table reports descriptive statistics for analysts forecast observations from 1999-2006. Analysts and forecast characteristics are derived from detailed I/B/E/S data. Our sample is analysts that cover both banks and non-banks. We restrict the sample to forecasts issued no earlier than 1 year and no later than 30 days before the fiscal-year end. The firm characteristics are *Earn_Std*, earnings dispersion; *MV,* the market capitalization; *BTM*, the book to market and *Follow*, the number of analysts covering the firm. The analyst characteristics are *F_Horizon*, the number of days from the forecast date to the fiscal year-end; *dayElap*, the number of days since any analyst's prior forecast; *fr*, forecast frequency; *Firm_Exp*, the analyst's years of experience forecasting a particular firm's earnings; *Gen_Exp*, the analyst's overall years of forecasting experience; *Num_Co*, the number of companies the analyst follows in each year; *Num_Ind*, the number of two-digit SIC industries the analyst follows in each year, and *Num_Ana*, the number of analysts in the analyst's brokerage house each year. Panel A reports the descriptive statistics of the relative forecast bias (*Rel_DFB* for first and last forecast) and the absolute forecast bias (*Abs_DFB* for first and last forecast) for the full sample and separately for the sample of employers and non-employers. Panel B reports both the descriptive statistics for relative control variables and absolute control variables based on the first forecast sample. Panel C reports correlations among scaled characteristics. Below the diagonal we present correlations for the last forecast bias (*Rel_DFB*) and above the diagonal we present the correlations for the first forecast bias (*Rel_DFB*) all variables are adjusted for firm-year effects where necessary. The *p*-values are reported below the correlations in parentheses. All variable definitions are as reported in the Appendix above.

Panel A: Dependent Variable

	Full Sample						**Employer**			**Non-Employer**			
Variable	*n*	*Mean*	*S.D.*	*25th Q*	*Median*	*75th Q*	*n*	*Mean*	*S.D.*	n	*Mean*	*S.D.*	*Difference (t-test)*
Dependent Variable													
Rel_DFB (first forecast)	3652	-0.07	1.01	-0.50	0.00	0.37	1860	-0.02	1.06	1792	-0.11	0.95	0.09 (2.76***)
Rel_DFB (last forecast)	3225	0.01	2.12	-1.00	-0.20	0.60	1581	-0.06	2.17	1644	0.08	2.07	-0.14 (1.84*)
Abs_DFB (first forecast)	3778	0.24	1.45	-0.23	-0.02	0.29	1943	0.32	1.60	1835	0.16	1.27	0.16 (3.29***)
Abs_DFB (last forecast)	3832	0.05	0.59	-0.09	-0.01	0.04	1956	0.03	0.34	1876	-0.01	0.40	0.04 (3.34***)

Panel B: Independent Variables

	Full Sample						Employer			Non-Employer		
Variable	*n*	*Mean*	*S.D.*	*25th Q*	*Median*	*75th Q*	*n*	*Mean*	*S.D.*	*n*	*Mean*	*S.D.*
Variables for the Rel_DFB analysis:												
Earn_Std	3652	0.07	0.04	0.05	0.07	0.10	1860	0.07	0.03	1792	0.08	0.04
Ln(MV)	3652	9.73	0.97	8.95	9.65	10.49	1860	10.00	1.00	1792	9.45	0.84
Ln(BTM)	3652	-0.90	0.42	-1.15	-0.82	-0.59	1860	-0.88	0.41	1792	-0.92	0.43
Ln(Follow)	3652	3.16	0.27	3.00	3.22	3.33	1860	3.19	0.28	1792	3.12	0.25
F_Horizon	3652	0.01	0.25	-0.13	0.04	0.18	1860	0.02	0.25	1792	0.01	0.25
dayElap	3652	0.58	2.87	-1.00	-0.82	0.50	1860	0.57	2.83	1792	0.60	2.92
fr	3652	-0.05	0.37	-0.33	-0.10	0.20	1860	-0.05	0.37	1792	-0.04	0.37
Firm_Exp	3652	0.02	0.79	-0.59	-0.20	0.36	1860	0.04	0.81	1792	0.01	0.77
Gen_Exp	3652	0.05	0.68	-0.49	-0.13	0.48	1860	0.02	0.65	1792	0.09	0.70
Num_Co	3652	0.22	0.57	-0.20	0.08	0.49	1860	0.20	0.55	1792	0.25	0.59
Num_Ind	3652	0.39	0.74	-0.14	0.00	0.78	1860	0.41	0.77	1792	0.36	0.71
Num_Ana	3652	-0.75	0.15	-0.88	-0.79	-0.64	1860	-0.76	0.15	1792	-0.75	0.16
Variables for the Abs_DFB analysis:												
Earn_Std	3778	0.08	0.04	0.05	0.07	0.10	1943	0.07	0.04	1835	0.08	0.05
Ln(MV)	3778	9.69	1.06	8.94	9.64	10.44	1943	9.97	1.13	1835	9.41	0.89
Ln(BTM)	3778	-0.91	0.50	-1.15	-0.82	-0.59	1943	-0.90	0.47	1835	-0.93	0.54
Ln(Follow)	3778	3.14	0.32	3.00	3.22	3.37	1943	3.17	0.35	1835	3.11	0.28
F_Horizon	3778	289.51	74.01	265.00	301.00	359.00	1943	289.63	75.03	1835	289.39	72.92
dayElap	3778	5.49	9.89	0.00	1.00	6.00	1943	5.32	9.74	1835	5.67	10.05
fr	3778	4.14	2.02	3.00	4.00	5.00	1943	4.25	2.05	1835	4.02	1.98
Firm_Exp	3778	4.45	3.74	2.00	3.00	6.00	1943	4.37	3.65	1835	4.53	3.84
Gen_Exp	3778	8.03	5.05	4.00	7.00	11.00	1943	7.82	4.74	1835	8.25	5.35
Num_Co	3778	21.28	12.67	13.00	18.00	25.00	1943	20.41	11.05	1835	22.20	14.13
Num_Ind	3778	2.25	1.50	1.00	2.00	3.00	1943	2.06	1.39	1835	2.45	1.58
Num_Ana	3778	42.14	27.84	20.00	35.00	57.00	1943	41.40	27.52	1835	42.92	28.15

Panel C: Correlations among scaled forecast, firm characteristics and analyst characteristics

	Rel_DFB	*EMPLOYER*	*Earn_Std*	*Ln(MV)*	*Ln(BTM)*	*Ln(Follow)*	*F_Horizon*	*dayElap*	*fr*	*Firm_Exp*	*Gen_Exp*	*Num_Co*	*Num_Ind*	*Num_Ana*
Rel_DFB		0.0456	0.0064	0.0217	0.0214	0.0390	0.2074	0.0061	0.1139	0.0329	0.0399	0.0319	0.0447	-0.0027
		(0.006)	(0.697)	(0.191)	(0.195)	(0.018)	(<0.001)	(0.714)	(<0.001)	(0.047)	(0.016)	(0.054)	(0.007)	(0.870)
EMPLOYER	-0.0252		-0.0478	0.2835	0.0467	0.1215	0.0161	-0.0042	-0.0114	0.0196	-0.0501	-0.0451	0.0379	-0.0251
	(0.153)		(0.004)	(<0.001)	(0.005)	(<0.001)	(0.331)	(0.801)	(0.508)	(0.236)	(0.003)	(0.006)	(0.022)	(0.129)
Earn_Std	0.0672	-0.0507		-0.1730	-0.1597	0.0119	0.0006	0.0247	0.0904	0.0031	0.0020	-0.0248	0.0100	0.1376
	(<0.001)	(0.004)		(<0.001)	(<0.001)	(0.474)	(0.971)	(0.136)	(<0.001)	(0.853)	(0.903)	(0.134)	(0.545)	(<0.001)
Ln(MV)	-0.0259	0.3486	-0.1207		-0.0296	0.5886	-0.0328	-0.0266	-0.0943	-0.1241	-0.1591	-0.0041	-0.0043	0.0163
	(0.142)	(<0.001)	(<0.001)		(0.073)	(<0.001)	(0.048)	(0.108)	(<0.001)	(<0.001)	(<0.001)	0.8035	0.7929	0.3247
Ln(BTM)	-0.0251	0.0766	-0.2316	-0.0313		0.1142	-0.0127	0.0259	-0.0364	-0.0024	-0.0431	0.0245	0.0336	-0.0887
	(0.155)	(<0.001)	(<0.001)	(0.075)		(<0.001)	(0.444)	(0.118)	(0.034)	(0.883)	(0.009)	(0.138)	(0.042)	(<0.001)
Ln(Follow)	0.0318	0.2496	0.0350	0.5682	0.0867		-0.0424	-0.0224	-0.0806	-0.1092	-0.1487	-0.0309	-0.0510	0.0071
	(0.071)	(<0.001)	(0.047)	(<0.001)	(<0.001)		(0.010)	(0.177)	(<0.001)	(<0.001)	(<0.001)	(0.062)	(0.002)	(0.667)
F_Horizon	0.1310	0.0517	0.0532	0.0822	-0.0127	0.0329		-0.0263	0.4288	0.1690	0.1306	0.0634	0.0142	0.0066
	(<0.001)	(0.003)	(0.003)	(<0.001)	(0.471)	(0.062)		(0.113)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.391)	(0.690)
dayElap	0.0270	0.0094	0.0062	-0.0193	-0.0070	-0.0237	-0.1529		-0.0018	0.0302	0.0999	0.0306	0.0409	-0.0503
	(0.126)	(0.593)	(0.727)	(0.273)	(0.692)	(0.178)	(<0.001)		(0.294)	(0.068)	(<0.001)	(0.064)	(0.014)	(0.002)
fr	0.0965	-0.0105	0.0545	-0.0987	-0.0331	-0.0742	0.4422	-0.0552		0.0577	0.0349	0.0204	-0.0718	0.0206
	(<0.001)	(0.547)	(<0.001)	(<0.001)	(0.0574)	(<0.001)	(<0.001)	(0.002)		(<0.001)	(0.415)	(0.235)	(<0.001)	(0.230)
Firm_Exp	0.0257	0.0047	-0.0038	-0.1222	0.0063	-0.0966	0.0152	0.0900	0.0607		0.5883	0.169	0.0206	-0.0194
	(0.145)	(0.788)	(0.829)	(<0.001)	(0.720)	(<0.001)	(0.389)	(<0.001)	(<0.001)		(<0.001)	(<0.001)	(0.213)	(0.242)
Gen_Exp	0.0160	-0.056	-0.0078	-0.1504	-0.0206	-0.1393	0.0210	0.1095	0.0288	0.6185		0.2972	0.0650	0.0338
	(0.364)	(0.002)	(0.660)	(<0.001)	(0.242)	(<0.001)	(0.234)	(<0.001)	(0.098)	(<0.001)		(<0.001)	(<0.001)	(0.041)
Num_Co	0.0273	-0.0321	-0.0307	-0.0281	0.0260	-0.0594	0.0088	0.0361	0.0340	0.1728	0.2851		0.4334	-0.0434
	(0.122)	(0.069)	(0.082)	(0.111)	(0.140)	(0.001)	(0.616)	(0.040)	(0.052)	(<0.001)	(<0.001)		(<0.001)	(0.009)
Num_Ind	0.0099	0.0326	-0.0006	-0.0102	0.0353	-0.0504	0.1013	0.0168	-0.0605	0.0270	0.0539	0.3983		-0.1043
	(0.576)	(0.065)	(0.974)	(0.563)	(0.045)	(0.004)	(<0.001)	(0.341)	(<0.001)	(0.125)	(0.002)	(<0.001)		(<0.001)
Num_Ana	0.0058	-0.0256	0.1339	0.0075	-0.1294	-0.0014	-0.0038	-0.0514	0.0219	-0.0056	0.0546	-0.0168	-0.0892	
	(0.742)	(0.146)	(<0.001)	(0.669)	(<0.001)	(0.935)	(0.828)	(0.004)	(0.210)	(0.749)	(0.002)	(0.339)	(<0.001)	

Table 2:

Comparing analyst forecast bias of bank-analysts first and last yearly earnings forecast

$DFB_{ijt}=\beta_1 EMPLOYER+\beta_2 Earn\_Std_{jt}+\beta_3 Ln(MV_{jt})+\beta_4 Ln(BTM_{jt})+\beta_5 Ln(Follow_{jt})+\beta_6 F\_Horizon_{ijt}+\beta_7 dayElap_{ijt}+\beta_8 fr_{ijt}+\beta_9 Firm\_Exp_{ijt}+\beta_{10} Gen\_Exp_{ijt}+\beta_{11} Num\_Co_{ijt}+\beta_{12} Num\_Ind_{ijt}+\beta_{13} Num\_Ana_{ijt}+\beta_{14} Year\ F.E. +\beta_{15} Analysts\ F.E. +\varepsilon_{ijt}$

Panel A: Full Sample

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
EMPLOYER	**0.090****	**-0.226***	**0.104*****	**-0.179*****
	(2.33)	**(-1.73)**	**(2.27)**	**(-2.43)**
Earn_Std	-0.437	3.694	10.420***	28.273***
	(-0.06)	(1.25)	(8.60)	(6.59)
Ln(MV)	-0.008	-0.238***	-0.032	-0.204**
	(-0.31)	(-2.61)	(-1.00)	(-3.17)
Ln(BTM)	0.045	-0.051	0.330***	-0.619***
	(0.89)	(-0.25)	(5.34)	(-3.98)
Ln(Follow)	0.247***	1.076***	0.346***	0.957***
	(2.72)	(2.95)	(2.82)	(4.35)
F_Horizon	0.959***	0.557***	0.000	0.003***
	(9.78)	(3.76)	(1.00)	(4.76)
dayElap	0.007	0.077**	-0.002	0.006**
	(1.13)	(2.59)	(-0.85)	(2.09)
fr	-0.002	-0.000	0.092***	-0.017
	(-1.46)	(-0.02)	(5.52)	(-0.65)
Firm_Exp	-0.030	0.208*	0.032***	0.019
	(-0.97)	(1.77)	(3.17)	(1.58)
Gen_Exp	0.079	0.025	0.329*	0.266
	(1.15)	(0.10)	(3.50)	(1.51)
Num_Co	0.090	-0.119	-0.008	0.005
	(1.54)	(-0.49)	(-1.33)	(0.90)
Num_Ind	0.036	-0.310*	-0.029	-0.028
	(1.08)	(-1.97)	(-0.77)	(-0.38)
Num_Ana	-0.352	0.084	-0.002	-0.000
	(-1.27)	(0.08)	(-0.74)	(-0.04)
Year F.E.	Yes	Yes	Yes	Yes
Analysts F.E.	Yes	Yes	Yes	Yes
Observations	3644	3212	3772	3819
Adjusted R^2	5.40%	1.70%	22.4%	25.0%

This table reports the ordinary least squares estimation results using two alternative measures of forecast bias; relative and absolute, for the period 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix above.

Panel B: Banks Only Sample

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
EMPLOYER	**0.090****	**-0.236***	**0.107*****	**-0.272*****
	(2.26)	**(-1.80)**	**(2.31)**	**(-3.32)**
Earn_Std	-0.428	2.120	11.224***	0.430
	(-0.54)	(0.66)	(8.62)	(0.87)
Ln(MV)	-0.014	-0.258***	-0.011	0.305*
	(-0.72)	(-2.69)	(-0.34)	(1.88)
Ln(BTM)	0.011	-0.021	0.306***	-0.654***
	(0.19)	(-0.10)	(4.44)	(-3.99)
Ln(Follow)	0.291***	1.074***	0.362***	2.089***
	(2.95)	(2.74)	(2.60)	(3.24)
F_Horizon	1.002***	0.648***	0.000	0.003**
	(9.56)	(4.19)	(0.81)	(2.56)
dayElap	0.006	0.082***	-0.001	0.005*
	(0.81)	(2.58)	(-0.50)	(1.75)
fr	-0.001	-0.006	0.090***	0.030
	(-1.18)	(-1.07)	(5.13)	(0.89)
Firm_Exp	-0.044	0.144	0.027***	-0.008
	(-1.35)	(1.22)	(2.57)	(-0.66)
Gen_Exp	0.084	0.201	0.416***	0.019
	(1.10)	(0.70)	(4.06)	(1.30)
Num_Co	0.068	-0.138	-0.007	-0.018***
	(1.06)	(-0.53)	(-1.14)	(-3.64)
Num_Ind	0.043	-0.393***	-0.041	0.207***
	(1.21)	(-2.41)	(-1.02)	(3.16)
Num_Ana	-0.251	0.521	-0.001	-0.935
	(-0.68)	(0.51)	(-0.33)	(-1.30)
Year F.E.	Yes	Yes	Yes	Yes
Analysts F.E.	Yes	Yes	Yes	Yes
Observations	3311	2934	3412	3447
Adjusted R^2	5.7%	1.0%	24.2%	27.3%

This table reports the ordinary least squares estimation results using two alternative measures of forecast bias; relative and absolute for the banking only sample 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix above.

Panel C: Pooling Observations across First and Last forecasts

Dependent Variable	***Rel_DFB***	***Abs_DFB***
	(1)	(2)
EMPLOYER * LAST	**-0.224*** **	**-0.407*** **
	(-3.41)	**(-5.52)**
LAST	0.056	0.361***
	(0.80)	(3.85)
Earn_Std	0.787	20.585***
	(0.72)	(7.63)
Ln(MV)	0.131	-1.213***
	(1.25)	(-6.83)
Ln(BTM)	-0.018	1.465***
	(-0.15)	(7.05)
Ln(Follow)	0.601**	0.364***
	(3.67)	(2.67)
F_Horizon	0.465***	0.001***
	(7.74)	(3.93)
dayElap	0.013**	0.001
	(2.00)	(0.39)
fr	0.000	0.040**
	(0.09)	(2.47)
Firm_Exp	0.051	-0.002
	(1.50)	(-0.31)
Gen_Exp	0.002	0.054
	(0.02)	(1.31)
Num_Co	0.029	0.001
	(0.42)	(0.16)
Num_Ind	-0.017	-0.035
	(-0.38)	(-0.83)
Num_Ana	-0.124	0.002
	(-0.43)	(0.72)
Year F.E.	Yes	Yes
Analyst F.E.	Yes	Yes
Firm F.E.	Yes	Yes
Observations	6853	7574
Adjusted R^2	3.6%	31.4%

This table reports the ordinary least squares estimation results using two alternative measures of forecast bias; relative and absolute for the sample 1999-2006. *LAST* is an indicator variable equal to one for the last forecast revision analyst *i* issued for firm *j* in year *t* and zero otherwise. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All other variable definitions are as reported in the Appendix above.

Table 3:

Propensity Score Matching Results

Panel A: Effects of propensity score matching: Full sample, (*Rel_DFB)*

	Unmatched				Matched			
	Employer	Non-Employer			Employer	Non-Employer		
Variable	Mean	Mean	%Bias	t-test	Mean	Mean	%Bias	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First Forecast								
Market Value	34962	17632	68.20	22.10***	24165	24468	-1.20	-0.41
BTM	0.4667	0.4597	3.50	1.15	0.4570	0.4415	7.90	2.40**
Follow	25.098	23.035	36.70	11.94***	24.337	23.98	6.40	1.86*
Firm_Exp	4.4085	4.4727	-1.90	-0.61	4.3428	4.3778	-1.00	-0.30
Qspread	0.1391	0.1432	-2.60	-0.83	0.1422	0.1416	0.40	0.77
Turnover	1.2922	1.4423	-18.10	-5.91***	1.3594	1.3151	5.30	1.68*
Total Risk	0.0698	0.0754	-16.40	-5.34***	0.0728	0.0713	4.40	1.33
Zscore	342.13	279.34	18.40	5.90***	315.51	304.47	3.20	0.95
Last Forecast								
Market Value	39946	17951	69.10	19.52***	22558	22932	-1.20	-0.51
BTM	0.4472	0.4338	8.00	2.28**	0.4388	0.4372	1.00	0.24
Follow	26.342	23.601	49.80	14.14***	25.321	24.994	5.90	1.65*
Firm_Exp	4.4436	4.5989	-4.40	-1.26	4.3352	4.2068	3.70	0.97
Qspread	0.1525	0.1517	0.50	0.14	0.1459	0.1554	-5.50	-1.39
Turnover	1.148	1.273	-19.00	-5.40***	1.2262	1.2302	-0.60	-0.16
Total Risk	0.0706	0.0770	-16.60	-4.71***	0.0753	0.0723	7.80	2.02**
Zscore	414.24	317.46	18.30	5.18***	377.78	357.49	3.80	0.89

Panel B: Effects of propensity score matching: Bank only sample (*Rel_DFB*)

	Unmatched				**Matched**			
	Employer	Non-Employer	%Bias	t-test	Employer	Non-Employer	%Bias	t-test
Variable	Mean	Mean	%Bias	t-test	Mean	Mean	%Bias	t-test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First Forecast								
Market Value	35204	17982	67.40	19.85***	22299	22545	-1.00	-0.36
BTM	0.4677	0.4514	8.60	2.62***	0.4558	0.4467	4.90	1.43
Follow	25.378	23.617	32.40	9.77***	24.569	23.952	11.40	3.28***
Firm_Exp	4.4924	4.1989	8.70	2.64***	4.3983	4.4651	-2.00	-0.56
Qspread	0.1382	0.1441	-3.60	-1.09	0.1435	0.1376	3.60	1.03
Turnover	1.2476	1.4307	-22.50	-6.89***	1.3125	1.2806	3.90	1.21
Total Risk	0.0684	0.0748	-18.60	-5.68***	0.0721	0.0671	14.70	4.49***
Zscore	351.66	304.91	13.00	3.93***	329.44	332.21	-0.80	-0.22
ROA	0.0180	0.0250	-26.80	-8.24***	0.0185	0.0203	-6.80	-2.19**
Last Forecast								
Market Value	38086	18520	60.00	16.33***	21452	21186	0.80	0.38
BTM	0.4432	0.440	1.60	0.47	0.4289	0.4252	2.60	0.62
Follow	25.768	23.981	29.70	8.30***	24.753	24.049	11.70	3.12***
Firm_Exp	4.607	4.335	7.40	2.07**	4.4763	4.6926	-5.90	-1.52
Qspread	0.1689	0.1963	-8.90	-2.55**	0.1741	0.1650	2.90	1.08
Turnover	1.1503	1.3475	-21.90	-6.26***	1.2198	1.1939	2.90	0.38
Total Risk	0.0707	0.0807	-22.30	-6.41***	0.0751	0.0722	6.60	1.98**
Zscore	444.80	382.58	10.50	2.94***	423.36	415.60	1.40	0.34
ROA	0.0211	0.0258	-11.80	-3.30***	0.0230	0.0245	-4.00	-0.99

Panel C: Full Sample

$$DFB_{ijt}=\beta_1 EMPLOYER+\beta_2 Earn\_Std_{jt}+\beta_3 Ln(MV_{jt})+\beta_4 Ln(BTM_{jt})+\beta_5 Ln(Follow_{jt})+\beta_6 F\_Horizon_{ijt}+\beta_7 dayElap_{ijt}+\beta_8 fr_{ijt}+\beta_9 Firm\_Exp_{ijt}+\beta_{10} Gen\_Exp_{ijt}+\beta_{11} Num\_Co_{ijt}+\beta_{12} Num\_Ind_{ijt}+\beta_{13} Num\_Ana_{ijt}+\beta_{14} Year\ F.E.+\beta_{15} Analyst\ F.E. + \varepsilon_{ijt}$$

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
EMPLOYER	**0.171*** **	**-0.788** **	**0.164*** **	**-0.280** **
	(3.60)	**(-2.07)**	**(3.08)**	**(-2.48)**
Earn_Std	-1.246	10.306*	7.569***	34.498***
	(-1.21)	(1.65)	(4.77)	(5.25)
Ln(MV)	-0.030	-0.554***	0.111**	-0.769**
	(-0.84)	(-2.70)	(2.37)	(-4.13)
Ln(BTM)	0.002	-0.032	0.278***	1.316***
	(0.03)	(-0.06)	(3.85)	(4.70)
Ln(Follow)	0.194	1.906*	0.126	1.842***
	(1.53)	(1.75)	(0.97)	(4.15)
F_Horizon	1.101***	1.177***	-0.000	0.003***
	(8.82)	(3.67)	(0.16)	(3.30)
dayElap	0.018**	0.154***	-0.003	0.006
	(2.08)	(2.95)	(-1.32)	(1.12)
fr	-0.002*	0.008	0.115***	-0.003
	(-1.81)	(0.75)	(5.49)	(-0.96)
Firm_Exp	-0.058	0.334	0.015	0.012
	(-1.48)	(1.07)	(1.19)	(0.39)
Gen_Exp	0.087	-0.155	0.093	-0.144
	(0.99)	(-0.33)	(1.38)	(-0.84)
Num_Co	0.088	-0.449	0.001	-0.008
	(1.10)	(-0.94)	(0.21)	(-0.95)
Num_Ind	0.000	-0.838*	0.001	0.014
	(0.00)	(-1.67)	(0.01)	(0.10)
Num_Ana	0.241	3.687*	-0.003	0.001
	(0.64)	(1.71)	(-1.18)	(0.20)
Year F.E.	Yes	Yes	Yes	Yes
Analyst F.E.	Yes	Yes	Yes	Yes
Observations	2332	1900	2388	2426
Adjusted R^2	9.90%	5.50%	23.70%	39.2%

This table reports the ordinary least squares estimation results using two measure of forecast bias, relative and absolute, for the years 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix above.

Panel D: Banks Only Sample

Dependent Variable	***Rel_DFB***		***Abs_DFB***	
	(1)	(2)	(3)	(4)
	First Forecast	*Last Forecast*	*First Forecast*	*Last Forecast*
EMPLOYER	**0.119*****	**-0.549***	**0.187*****	**-0.271****
	(2.71)	**(-1.88)**	**(3.51)**	**(-2.45)**
Earn_Std	-0.099	7.612	4.304*	41.315***
	(-0.09)	(1.10)	(1.84)	(4.47)
Ln(MV)	-0.035	-0.606**	0.189***	-0.656***
	(-1.02)	(-2.90)	(3.40)	(-3.40)
Ln(BTM)	-0.091	0.542	0.160**	1.125***
	(-1.47)	(1.42)	(2.12)	(3.48)
Ln(Follow)	0.330**	0.780	0.148	0.809***
	(2.44)	(1.05)	(1.14)	(2.88)
F_Horizon	0.925***	0.829**	-0.000	0.002**
	(7.00)	(2.42)	(-1.03)	(2.45)
dayElap	0.006	0.260***	-0.002	0.005
	(0.73)	(2.82)	(-0.70)	(1.09)
fr	0.000	-0.007	0.138***	-0.059
	(0.07)	(-0.72)	(5.98)	(-1.52)
Firm_Exp	-0.059	0.342	0.031**	0.018
	(-1.46)	(1.45)	(2.48)	(0.62)
Gen_Exp	-0.017	-0.313	0.279**	-0.001
	(-0.18)	(-0.64)	(2.18)	(-0.00)
Num_Co	-0.042	-0.653	-0.010	0.003
	(-0.48)	(-1.51)	(-1.21)	(0.35)
Num_Ind	0.058	-0.315	0.000	-0.024
	(1.24)	(-1.05)	(0.01)	(-0.24)
Num_Ana	0.222	1.336	-0.000	-0.004
	(0.69)	(0.81)	(-0.15)	(-0.91)
Year F.E.	Yes	Yes	Yes	Yes
Analysts F.E.	Yes	Yes	Yes	Yes
Observations	2078	1764	2136	2142
Adjusted R^2	8.1%	1.1%	23.20%	30.30%

This table reports the ordinary least squares estimation results using two forecast bias measures: relative and absolute for a sub-sample of banks for the years 1999-2006. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by analyst. *t*-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively (two-tailed). All variable definitions are as reported in the Appendix above.

Table 4
Panel A: Comparing analyst forecast bias of bank-analysts first and last yearly earnings forecast before and after the Global Settlement

$$Rel\_DFB_{ijt} = \beta_1 EMPLOYER*POST + \beta_2 EMPLOYER + \beta_3 Earn\_Std_{jt} + \beta_4 Ln(MV_{jt}) + \beta_5 Ln(BTM_{jt}) + \beta_6 Ln(Follow_{jt}) + \beta_7 F\_Horizon_{ijt} + \beta_8 dayElap_{ijt} + \beta_9 fr_{ijt} + \beta_{10} Firm\_Exp_{ijt} + \beta_{11} Gen\_Exp_{ijt} + \beta_{12} Num\_Co_{ijt} + \beta_{13} Num\_Ind_{ijt} + \beta_{14} Num\_Ana_{ijt} + \beta_{15} Year\ F.E. + \beta_{16} Analyst\ F.E. + \varepsilon_{ijt}$$

	First Forecast	*Last Forecast*
	(1)	(2)
EMPLOYER*POST	**0.168****	**-0.155***
	(2.21)	**(-1.65)**
EMPLOYER	-0.039	0.051
	(-0.73)	(0.71)
Earn_Std	-0.763	0.997
	(-0.904)	(1.10)
Ln(MV)	0.033	0.008
	(1.18)	(0.23)
Ln(BTM)	0.072	0.118***
	(1.32)	(2.96)
Ln(Follow)	0.051	0.320***
	(0.52)	(2.92)
F_Horizon	0.927***	0.175***
	(8.31)	(4.85)
dayElap	0.002	-0.000
	(0.28)	(-0.05)
fr	-0.002*	-0.005***
	(-1.90)	(-2.85)
Firm_Exp	-0.028	0.006
	(-0.97)	(0.13)
Gen_Exp	0.053	-0.050
	(0.96)	(-0.88)
Num_Co	0.092	0.003
	(1.40)	(0.07)
Num_Ind	0.015	0.092*
	(0.39)	(1.74)
Num_Ana	-0.378	0.635
	(-1.16)	(-1.61)
Year F.E.	YES	YES
Analysts F.E.	YES	YES
Observations	3476	3154
Adjusted R^2	3.20%	9.70%

This table compares analyst bias before and after the Global Settlement in year 2003 using analyst constant sample from year 1999 to 2006. Before the settlement represents years 1999 to 2002 while after the settlement represents years 2004 to 2006. The year of the Global Settlement is excluded. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by company and analyst pair. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All variable definitions are as reported in the Appendix above.

Panel B: Sub-sample of firms that experienced no decrease in analyst coverage following the Global Settlement

	Before Global Settlement	
	First Forecast	*Last Forecast*
	(1)	(2)
EMPLOYER*POST	**0.144***	**-0.203***
	(1.88)	**(-1.62)**
EMPLOYER	-0.007	0.050
	(-0.14)	(0.67)
Earn_Std	-0.744	1.528
	(-0.90)	(1.46)
Ln(MV)	0.022	0.015
	(0.79)	(0.35)
Ln(BTM)	0.053	0.150***
	(0.96)	(3.24)
Ln(Follow)	0.028	0.340**
	(0.27)	(2.02)
F_Horizon	0.921***	0.179***
	(8.17)	(4.29)
dayElap	0.002	0.000
	(0.28)	(0.24)
fr	-0.002	-0.001
	(-1.56)	(-0.56)
Firm_Exp	-0.020	-0.019
	(-0.71)	(-0.39)
Gen_Exp	0.045	-0.054
	(0.81)	(-0.92)
Num_Co	0.097	0.006
	(1.45)	(0.06)
Num_Ind	0.012	0.031
	(0.31)	(0.44)
Num_Ana	-0.343	-0.521
	(-1.05)	(-1.08)
Year F.E.	YES	YES
Analysts F.E.	YES	YES
Observations	3428	2631
Adjusted R^2	3.20%	9.10%

This table compares analyst bias before and after the Global Settlement in year 2003 using analyst constant sample and excluding any firms that experienced a drop in analysts following after Settlement. Before the settlement represents years 1999 to 2002 while after the settlement represents years 2004 to 2006. The year of the Global Settlement is excluded. First forecast is the initial forecast analyst *i* issued for firm *j* in year *t* and last forecast is the last forecast revision analyst *i* issued for firm *j* in year *t*. Heteroskedasticity-robust standard errors are clustered by company and analyst pair. t-statistics are reported in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively. All variable definitions are as reported in the Appendix above.

Table 5
Brokerage House Status and Job Movement

Panel A: Percentage of analysts in different status brokerage houses each year
The table presents the percentage of all analysts in I/B/E/S who are categorized as working for high-status, median-status and low-status brokerage houses.

Brokerage House Status	High-status Brokerage House	Median-status Brokerage House	Low-status Brokerage House
Year	Analyst%	Analyst%	Analyst%
1999	27.33%	48.17%	24.49%
2000	26.44%	51.57%	21.99%
2001	30.62%	45.26%	24.13%
2002	33.12%	43.88%	23.01%
2003	33.31%	45.12%	21.57%
2004	35.02%	43.28%	21.70%
2005	33.95%	45.15%	20.90%
2006	32.51%	47.58%	19.91%
Overall (1998-2006)	31.53%	46.25%	22.21%

Panel B: Summary statistics of analyst job movement
This table presents the averaged percentage of all analyst and analysts who forecast potential employers in the I/B/E/S database who move between brokerage houses each year during 1999-2006 and the percentage who experience various types of job separations in a year averaged over year 1999-2006.

	All Analysts	Analysts forecasting Employers
	(1)	(2)
% of Analysts Who Change Houses each Year:	6.05%	6.93%
Average % of Analysts that move up each year	49.39%	51.35%
Average % of Analysts that move down each year	30.17%	29.73%
Average % of Analysts that stay high each year	11.32%	12.61%
Average % of Analysts that stay low each year	9.14%	4.50%
% of Analysts moving from High-Status House	16.32%	16.41%
% of Analysts moving from Low-Status House	24.61%	15.90%
% of Analysts moving from Mid-Status House	59.07%	67.69%

Panel C: The effect of relative forecast bias on job separations

$Move\_status_{t+1} = \beta_1\, BIAS_{ijt} + \beta_2 EMPLOYER + \beta_3\, BIAS_{ijt} * EMPLOYER + \beta_4 Gen\_Exp_{ijt} + \beta_5 Num\_Co_{ijt} + \beta_6 Accuracy + \beta_7 Status\ F.E. + \beta_8 Year\ F.E + \varepsilon_{ijt}$

Dependent Variable= *Move_status*	*Relative Forecast Bias*			
Variable	*First Forecast*		*Last Forecast*	
	Coefficient	*Odds Ratio or Ratios of odds ratios*	*Coefficient*	*Odds Ratio or Ratios of odds ratios*
	(1)	(2)	(3)	(4)
Rel_BIAS	0.000	1.000	-0.000	1.000
	(0.26)		(-0.29)	
EMPLOYER	0.915	2.496	1.366**	3.921*
	(1.45)		(2.20)	
Rel_BIAS*EMPLOYER	**-0.003**	**0.997**	**-0.339****	**0.712***
	(-0.05)		**(-2.30)**	
Gen_Exp	-0.029	0.971	-0.043**	0.957*
	(-1.37)		(-1.97)	
Num_Co	0.040**	1.041*	0.033*	1.033
	(2.35)		(1.87)	
Accuracy	-0.024	0.976	-0.127	0.881
	(-0.09)		(-0.49)	
Status F.E.	Yes		Yes	
Year F.E.	Yes		Yes	
Observations	568		512	
Pesudo-R^2	28.40%		27.60%	

This table present estimations from the ordinal logit regression to examine if past forecast optimism from bank and non-bank analysts have different effect on the likelihood of analyst moves to a higher or lower status brokerage house during 1999 to 2006. The sample contains only those analysts from medium or low status houses. The dependant variable *Move-status* equals the value 1 if the analyst in time *t* moves up one hierarchy of brokerage house status and the value of 2 if the move up represents a move of two hierarches. If the analyst moves side-ways then it takes the value of zero. If, however, the analysts moves down one hierarchy then it takes the value of -1. Similar with Hong and Kubik (2003), we measure the forecast bias for each firm the analyst forecasts in year *t* minus the average bias of analysts from the high-status house who follow the firms, which we then average across the stocks that the analysts covers which provides us with a bias measure for analysts *i* in year *t*. The *Rel_BIAS* variable is the average of this relative forecast bias in year *t* and the two previous years. Analysts who have less than three prior years of experience are therefore excluded. *Accuracy* is a dummy variable taking the value of 1 if the analyst is ranked in the top 10% in terms of their average 3 year forecast accuracy and zero otherwise. All other variables are as defined in the Appendix. Heteroskedasticity-robust standard errors are clustered by company and analyst pair. *, **, and *** represent significance level of 5%, 1%, and 0.1%, respectively (two-tailed).

Panel D: The effect of absolute forecast bias on job separations

Dependent Variable= *Move_status*	*Absolute Forecast Bias*			
Variable	*First Forecast*		*Last Forecast*	
	Coefficient	*Odds Ratio or Ratios of odds ratios*	*Coefficient*	*Odds Ratio or Ratios of odds ratios*
	(1)	(2)	(3)	(4)
Abs_BIAS	-0.094	0.911	0.038	1.039
	(-1.13)		(0.15)	
EMPLOYER	0.810	2.248	1.345**	3.839*
	(1.24)		(2.32)	
Abs_BIAS*EMPLOYER	**0.138**	**1.148**	**-2.532***	**0.0795***
	(0.31)		**(-1.89)**	
Gen_Exp	-0.028	0.972	-0.045**	0.956*
	(-1.33)		(-2.02)	
Num_Co	0.040**	1.040*	0.034*	1.034
	(2.35)		(1.95)	
Accuracy	0.112	1.118	0.055	1.057
	(0.49)		(0.26)	
Status F.E.	YES		YES	
Year F.E.	YES		YES	
Observations	568		516	
Pesudo-R^2	28.2%		27.4%	

This table present estimations from the ordinal logit regression to examine if past forecast optimism from bank and non-bank analysts have different effect on the likelihood of analyst moves to a higher or lower status brokerage house during 1999 to 2006. The sample contains only those analysts from medium or low status houses. The dependant variable *Move-status* equals the value 1 if the analyst in time *t* moves up one hierarchy of brokerage house status and the value of 2 if the move up represents a move of two hierarches. If the analyst moves side-ways then it takes the value of zero. If, however, the analysts moves down one hierarchy then it takes the value of -1. Similar with Hong and Kubik (2003), we measure the forecast bias for each firm the analyst forecasts in year *t*, which we then average across the stocks that the analysts covers which provides us with a bias measure for analysts *i* in year *t*. The *Abs_BIAS* variable is the average this forecast bias in year *t* and the two previous years. Analysts who have less than three prior years of experience are therefore excluded. *Accuracy* is a dummy variable taking the value of 1 if the analyst is ranked in the top 10% in terms of their average 3 year forecast accuracy and zero otherwise. All other variables are as defined in the Appendix. Heteroskedasticity-robust standard errors are clustered by company and analyst pair. *, **, and *** represent significance level of 5%, 1%, and 0.1%, respectively (two-tailed).