Privileged Access, Conflict of Interest, and Analyst Career Concerns: Evidence from Regulatory Change

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Abstract

This paper studies the dynamic effects of conflict of interest and privileged access on earnings forecast bias. When conflicts exist, analysts increase bias with tenure. Privileged access through underwriter affiliation also affects dynamic behavior – affiliated analysts are more conservative than unaffiliated analysts in early periods and more biased in late periods. Regulation Fair Disclosure (Reg FD) provides an experiment for identifying the role of privileged access. The privileged access result is driven by the pre-Reg FD period. In the post-Reg FD period, both analyst types increase bias at a similar rate. Analysts influence investors; zero-investment tenure portfolios provide significant alphas.

Key words: Privileged Access, Analyst Bias, Conflicts of Interest, Career Concerns, Regulation

JEL Classification: G12, G18, G28, G29, M49.

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1. Introduction

Rarely can any investor be as well informed about a firm as a manager with inside information. To bridge this information gap, the investor consults a financial analyst for guidance (Bolton, Freixas, and Shapiro, 2007; Malmendier and Shanthikumar, 2007a). While the analyst is expected to provide unbiased predictions of a firm's earnings, he tends to be too optimistic in these earnings forecasts. The investor is subsequently influenced and negatively impacted by analyst optimism (Ackert and Athanassakos, 1997; De Franco, Lu, and Vasvari, 2007).

Research finds that analyst optimism, or positive earnings forecast bias, is associated with three factors. An analyst making forecasts of firm earnings may be biased under the influence of that firm's investment banking relationship with his employer (Lin and McNichols, 1998). An analyst may also be biased in order to bolster trading revenue (Hayes, 1998). Both factors are potential conflicts of interest. The concern for privileged access can also play a role in analyst bias (Francis and Philbrick, 1993). What are the effects of conflict of interest and privileged access on bias in a dynamic setting[1]? Are investors influenced by the dynamic effect of analyst conflict of interest?

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[1] Research attempting to explain earnings forecast bias is mostly static in approach. A static approach interprets analyst behavior irrespective of the analyst's progress in his career cycle. A dynamic approach explicitly addresses how an analyst behaves over the course of his career.

The dynamic moral hazard model is a particularly attractive framework for answering these questions. Consider the following adaptation to analyst career concerns. Two sources of compensation motivate the analyst: generating a reputation for accuracy, and generating revenue for his employer (Groysberg, Healy and Maber, 2008). The labor market compensates the analyst for his ability to be accurate, but no one observes analyst ability, not even the analyst. The labor market must therefore estimate ability. High ability analysts are likely to be less biased than low ability analysts. Analyst bias is determined in equilibrium and analysts are motivated to be conservative through the concern for generating a reputation for accuracy.

Conflict of interest now presents the analyst with a tradeoff that impacts his entire career and shapes his incentives to be biased. Bias is a double-edged sword; on one hand, bias benefits the analyst through potential conflict of interest. On the other hand, bias reduces accuracy, which in turn has a negative impact on the analyst's reputation. The first result is that the analyst will be conservative in early periods when the impact of bias on reputation is high, but optimistic in late periods when the impact of bias on reputation is low.

Now ponder the role of privileged access. There are two direct effects of privileged access: one obvious, one not. Analysts with privileged access (privileged analysts) surely have an information advantage over analysts without privileged access (restricted analysts). More importantly though, privileged access allows the privileged employer to be privy to information that restricted employers do not possess. The latter effect makes the privileged employer a better judge of analyst ability when compared to a restricted employer. In other words, privileged employers are more precise when estimating analyst ability. This difference in precision creates an employer information hierarchy in the labor market with respect to analyst evaluation.

Through this information hierarchy, privileged access has a dynamic effect on the difference in analyst forecast bias between privileged analysts and restricted analysts. For ease of exposition, let's say that analysts are randomly assigned to privileged and restricted employers in each period[2]. In the first period, employer assignment is given and all employers use Bayesian updating to estimate analyst ability. Compare a privileged analyst to a restricted analyst. In the absence of a reputation, a higher level of precision engenders stronger incentives to be conservative. Hence in early periods privileged analysts are likely to be more conservative than restricted analysts because privileged employers have a higher level of precision when compared to restricted employers.

Now consider what happens in late periods when the reputation earned in earlier periods impacts on the analyst's incentives to be biased. Compare an analyst who has always been privileged to an analyst who has always been restricted. The privileged analyst's reputation is stronger (more precise) that the restricted analyst's reputation. As reputation strength increases, the analyst has less of an incentive to be conservative. Privileged analyst reputation strength is greater than restricted analyst reputation strength, so privileged analysts are likely to be more biased than restricted analysts in late periods.

[2] The model presented in the Appendix relaxes this assumption, but gives the same hypotheses presented in the main body of the paper.

The potential for conflict of interest is present for all analysts. The theoretical model provides three testable hypotheses on the effects of tenure and privileged access on earnings forecast bias. In testing the impact of privileged access, a complication arises. All analysts are likely to herd at the start of the career cycle (Hong, Kubik, and Solomon, 2000; Avery and Chevalier, 1999), which limits the effectiveness of the linear model in testing the impact of privileged access. Therefore, to study the tenure-bias relationship, in addition to a model with a linear specification, I use a semiparametric partial linear regression model with a flexible specification for tenure.

Annual earnings forecast bias increases over the course of an analyst's career. This result is robust controlling for the misweighting of information (prior forecast error, forecast frequency), analyst ability (analyst fixed effects, forecast frequency), analyst coverage (firm fixed effects), and year, broker, and industry fixed effects.

Using underwriter affiliation as a proxy for privileged status (Allen and Faulhaber, 1989; Michaely and Womack, 1999), I show that at the start of the career cycle, affiliated analyst bias is less than unaffiliated analyst bias. Towards the end of the career cycle, the difference in bias between affiliated analysts and unaffiliated analysts increases.

Is this particular result driven by an information hierarchy? If so, reducing the information benefit for affiliated analysts should result in very little difference in the rate of change of bias with tenure between affiliated analysts and unaffiliated analysts. Since Reg FD was designed to prevent selective disclosure, the adoption of Reg FD on October 23, 2000, is used as a natural experiment to test this hypothesis. With respect to the rate of change of bias with tenure, the evidence shows little difference between unaffiliated analysts and affiliated analysts in the post-Reg FD period. These results are robust controlling for the misweighting of information (prior forecast error, forecast frequency), analyst ability (analyst fixed effects, forecast frequency), analyst coverage (firm fixed effects), and year, broker, and industry fixed effects.

The paper also provides evidence that suggests that investors are influenced by the bias motivated through career concerns. The strategy of buying an equal-weighted portfolio of firms in the lowest analyst tenure tercile and selling an equal-weighted portfolio of firms in the highest analyst tenure tercile earns an abnormal return of approximately 1% per month. This result is robust controlling for differences in analyst coverage between untenured analysts and tenured analysts and is driven by the stocks that are the most difficult to value: glamour stocks. This finding suggests that for the most opaque firms, market participants are influenced by conflict of interest and analyst career concerns; they do not adjust their expectations downward for bias.

This paper makes a number of contributions. It is the first paper to use an information hierarchy in a dynamic moral hazard model. Using this model, the paper is the first to take both conflict of interest and privileged access into account to show the impact of each factor in a dynamic setting. It is the first paper to show that investors are influenced by potentially conflicted analyst bias through dynamic incentives. By using a natural experiment approach, this is the first paper to test the effect of an information hierarchy on labor market outcomes (the effect of privileged access on analyst bias). In doing so, the paper provides a robust economic explanation of the impact of Reg FD on analyst bias in a dynamic setting.

2. Related Literature

There are papers that study analyst performance in a dynamic setting (Hong and Kubik, 2003; Clarke and Subramanian, 2006). These papers are based on a dynamic moral hazard model with agent "career concerns." Holmstrom (1982, 1999) originally introduced a dynamic moral hazard model[3] where the agent and the labor market learn about the agent's ability over time. One key result of the model is that the agent's wage increases with tenure (Holmstrom, 1982). Another result of the model is that the agent's effort decreases with tenure (Holmstrom, 1999).

Hong and Kubik (2003) argue that the analyst labor market is subject to dynamic learning and show that over time, a relatively accurate forecaster is rewarded more than a less accurate forecaster. Hong, Kubik, and Solomon (2000) argue that dynamic incentives motivate inexperienced or untenured analysts to make similar forecasts. Clarke and Subramanian (2006) show that in a dynamic model, the presence of employment risk leads to a U-shaped relationship between forecast boldness and prior accuracy. Chen and Jiang (2006) argue that the misweighting of private information is an important factor in analyst performance; analysts are less likely to misweight private information at the start of the career cycle in a dynamic model.

[3] Holmstrom (1999) shows that when ability is unknown to all and effort is costly to the worker, the concern for reputation-building motivates the worker to work hard early in his career and less so in the years approaching retirement. This pattern arises from a tradeoff between the reputation-building benefits of worker output and the cost of worker effort.

An alternative approach to study analyst performance in a dynamic setting is that of learning-by-doing; an analyst's performance may improve as he gains experience[4]. The evidence on this issue is mixed. Some studies find a positive effect on performance (Mikhail, Walther, and Willis, 1997; Clement, 1999), while others do not (Jacob, Lys, and Neale, 1999; Hong, Kubik, and Solomon, 2000).

In contrast to papers that study the dynamic impact of various factors on analyst performance in general, the papers that study earnings forecast bias are mostly static in approach. Two determinants in particular have been shown to contribute to analyst bias: privileged access (underwriter affiliation) and potential conflict of interest (underwriter affiliation and trading commissions).

Lin and McNichols (1998), Allen and Faulhaber (1989), Hayes (1998), Jackson (2005), Beyer and Guttman (2007), and Groysberg, Healy and Maber, 2008 all study the effect of potential conflict of interest on analyst bias. In studying the effect of underwriter affiliation, Lin and McNichols (1998) show that there is no difference in year-ahead earnings forecasts based on affiliation status. Hayes (1998) and Jackson (2005) argue that bias caused by potential conflict of interest need not be related to underwriter affiliation; the concern to generate trading revenue may influence analysts to make biased earnings forecasts. Beyer and Guttman (2007) provide a theory of the effect of trading commissions on analyst bias. In their model, analysts balance the

[4] Experience can be defined as company-specific or general. General experience can be measured much in the same way that I measure tenure. Henceforth I refer to my measure as tenure to distinguish my approach from the learning-by-doing studies.

benefit from trading commissions against the cost from forecast errors. Cowen, Groysberg, and Healy (2006) use data on different analyst employer types to show that retail brokerage analysts are the most biased group. They conclude that analyst bias is in part driven by incentives to generate trading commissions.

Trading commissions and underwriter affiliation are not the only factors that contribute to forecast bias. Francis and Philbrick (1993) and Lim (2001) show that an analyst may be biased in order to gain privileged access, ultimately in an effort to minimize forecast error. Allen and Faulhaber (1989) and Michaely and Womack (1999) argue that underwriter affiliation may not only be a source of potential conflict of interest; it may also provide analysts with privileged access to managers of covered firms.

In testing the model predictions for the effect of privileged access, this paper adds to the literature on the impact of equal access regulation (Heflin, Subramanyam, and Zhang, 2003; Bailey et al., 2003; Mohanram and Sunder, 2006; Cohen, Frazzini, and Malloy, 2008). In a paper that looks at the cross-sectional impact based on brokerage size, Mohanram and Sunder (2006) show a reduction in forecast accuracy for large brokerage analysts who likely benefited the most from privileged access in the pre-Reg FD period. Cohen, Frazzini, and Malloy (2008) find that analysts were able to exploit their social networks to gather private information in the pre-Reg FD period. They show that the return premium to recommendations from analysts with a strong social network is positive and significant in the pre-Reg FD period, but zero and insignificant in the post-Reg FD period.

Finally, this paper adds to the literature on the market reaction to analyst forecasts and recommendations (Ackert and Athanassakos, 1997; Lin and McNichols, 1998; De Franco, Lu, and Vasvari, 2007). Ackert and Athanassakos (1997) provide evidence that the market does not adjust for analyst earnings forecast bias. They show that the price of a high bias firm is bid up by investors around the time of the analyst's forecast; subsequent returns are lower.

3. Data

The sample period used in this paper is 1993 to 2005. Analysts' annual year-ahead (*I/B/E/S* Field - FY1) earnings forecasts are sourced from the *Institutional Brokers Estimate System (I/B/E/S)* Dataset. Forecasts for firms with missing actual EPS in the *I/B/E/S* database are removed from the final sample. The Detail History File records the individual analyst forecasts, an identification code unique to the analyst, the identity of firms they follow, a broker identification code and the forecast dates. In order to identify the broker, the Detail History File is merged with the Recommendation Detail File by the analyst identification code which is common to both files.

Balance sheet and industry code data are obtained from *Compustat* for the firms taken from the *I/B/E/S* database. The *Standard & Poor's* Global Industry Classification (GIC) industry codes are obtained from the *Compustat* Segment File. Each firm in the *I/B/E/S* data is assigned to one of the many industries classified by using the leftmost four digits of the eight-digit GIC codes. GIC codes provide a good proxy for analysts' industry specialization (Boni and Womack, 2006), and can explain the cross-sectional differences in firms' valuation multiples, financial ratios, and forecasted growth rates (Bhojraj, Lee, and Oler, 2003). For a given year, forecasts for firms with missing data for industry classification or market capitalization are removed from the final sample.

In order to determine underwriting affiliation, initial and secondary offerings of equity are sourced from *SDC*. The lead manager names are then matched with the broker names for the analysts. To account for mergers, the *SDC* Merger & Acquisition (M&A) database is used to compile a list of mergers between financial institutions[5]. *Factiva* is also used as an internet source for news on any merger events involving the brokerages in the sample.

In order to be included in the final sample, I require that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm of interest. This requirement serves to control for the difference in analyst coverage between affiliated analysts and unaffiliated analysts. The final sample consists of 95,401 annual analyst forecast observations.

Stock price and return data for firms in the sample are sourced from the *Center for Research in Security Prices (CRSP)*. Finally, returns for factor mimicking portfolios are sourced from Kenneth French's website and extracted through the *Wharton Research Data Services (WRDS)* web portal.

[5] To account for M&A between the brokerages in the sample, the target is assigned the broker family code of the acquirer after the effective merger deal date. For example, Cowen & Co. is assigned the same broker family as Societe Generale Securities after the effective deal date of June 30, 1998.

4. Methodology

The dynamic moral hazard framework imposes no specific functional form for the relationship between the career time (tenure) and the dependent variable (analyst earnings forecast bias). Moreover, analysts herd at the start of the career cycle (Hong, Kubik, and Solomon, 2000). For these reasons, a semiparametric approach is particularly attractive. The partial linear regression (PL) model presented here is semiparametric in that linearity need only be imposed on the control variables (Engel et al., 1986). This model has been used in a number of papers in applied microeconomics (Deaton and Paxson, 1998; Yatchew and No, 2001; Pence, 2006) and finance (Chevalier and Ellison, 1997).

The PL model can be estimated by a two part Ordinary Least Squares-Kernel estimator (Robinson, 1988). I estimate the PL model using a difference estimator (Yatchew, 1997, 1998). Yatchew and No (2001) show that differencing techniques significantly simplify estimation and testing and provide similar results to Robinson's method.

Consider the following parametric model, where z is the independent variable of interest.

$$y_i = \gamma z_i + \boldsymbol{X}_i \beta + \varepsilon_i \tag{1}$$

Here, z is a random variable, $\boldsymbol{X}$ a K-dimensional vector of control variables, and ε, an independently and identically distributed mean zero noise term. In this familiar model, a linearity restriction is imposed for the relationship between z and y. Let us relax this restriction in favor of the following flexible model. For the ease of exposition, assume that all variables are scalars.

$$y_i = g(z_i) + x_i\beta + \varepsilon_i, \quad \text{where} \tag{2}$$

$$E[y_i|z_i, x_i] = g(z_i) + x_i\beta \quad \text{and} \quad Var[y_i|z_i, x_i] = \sigma_\varepsilon^2$$

This PL model now allows for the data to determine the functional form of the relationship between z and y. The function $g(z)$ is thus a smooth single-valued function with a first derivative bounded by a constant, L. In this model, $g(z_i)$ and $x_i\beta$ are additively separable and z is not perfectly correlated with x. See Yatchew (1998) for implementation details regarding the difference estimator for the PL model.

5. Sample Statistics and Empirical Analysis

Each observation represents the forecast bias for an analyst's annual (year-ahead) EPS forecast. Following Ackert and Athanassakos (1997), the dependent variable: ex-post earnings forecast bias[6], is defined in the following manner.

$$BIAS_{ijt} = 100 * \left(\frac{F_{ijt} - E_{ijt}}{|E_{ijt}|}\right) \tag{12}$$

F_{ijt} and E_{ijt} are the EPS forecast and the actual EPS of the firm respectively, where *i* represents the analyst, *j* represents the firm, and *t* represents time. The affiliation status of the forecast is represented by a dummy variable equal to one if the analyst making the forecast is employed by the financial institution that was the lead manager for the most recent equity offering of the firm.

[6] In my model, the market uses ex-post forecast error to estimate ability. Hence the appropriateness of the ex-post measure for earnings forecast bias.

Bias is winsorized at the 5% level to reduce the impact of extreme values and tail asymmetry (Abarbanell and Lehavy, 2003).

This paper studies analyst forecast bias in terms of a dynamic moral hazard model with an information hierarchy. The model provides the following testable hypotheses where underwriter affiliation is used as a proxy for employers with privileged access (see the Appendix).

Hypothesis 1 (Bias and Tenure) For potentially conflicted analysts, bias increases with analyst tenure.

Hypothesis 2 (Affiliation, Bias and Tenure) In an environment of privileged access, affiliated analysts are less biased than unaffiliated analysts in early periods, and the difference in bias between affiliated analysts and unaffiliated analysts increases with analyst tenure.

Hypothesis 3 (The Impact of Regulation) Compared to the pre-Reg FD period (privileged access), in the post-Reg FD period (equal access) the difference in the tenure-bias slope between affiliated analysts and unaffiliated analysts is smaller.

Table 1 shows summary statistics for variables used for multivariate analysis. Panel A shows differences in means based on affiliation status. Affiliated analysts tend to be more tenured than their unaffiliated counterparts. The mean tenure for affiliated analysts is approximately eight years. The comparable figure for unaffiliated analysts is approximately seven years. The firms covered by affiliated analysts are smaller than those covered by unaffiliated analysts. The average market capitalization for firms covered by affiliated analysts is $7.7 billion for the sample period, whereas the average market capitalization for firms covered by unaffiliated analysts is $12.2 billion[7]. On average, the firms covered by affiliated analysts are less followed than those covered by unaffiliated analysts. The average analyst coverage number for unaffiliated analysts is approximately 17 in any given year, whereas the average analyst coverage number for affiliated analysts is approximately 13[8]. Each of these differences is statistically significant at the 1% level.

Table 1 Panel B shows differences in means based on tenure. Tenured analysts are defined as those that have tenure more than the median for the sample at the time of the forecast. Tenured analysts are more likely to be affiliated than their untenured counterparts. The mean affiliation measure for tenured analysts is 0.112. The comparable figure for untenured analysts is 0.076. On average, the firms covered by tenured analysts are less followed than those covered by untenured analysts. The average analyst coverage number for untenured analysts is approximately 17 in any given year, whereas the average analyst coverage number for tenured analysts is approximately 16. Each of these differences is statistically significant at the 1% level.

[7] This counterintuitive result can be explained by the sample construction method. A firm must be covered by an affiliated analyst to be included in the sample and there is a limit to the number of affiliated analysts for a given firm. Therefore, there will be more unaffiliated analysts for the larger firms in the sample.

[8] Ibid.

There is no statistically significant difference in the size of firms covered based on the dichotomous tenure variable.

Table 2 shows mean earnings bias by affiliation status and tenure tercile. As predicted by the model, the difference decreases as tenure increases. For the lowest tenure tercile, affiliated analysts are less biased than unaffiliated analysts; the average bias for unaffiliated analysts is approximately 12%, whereas the average bias for affiliated analysts is approximately 8%. For the third tenure tercile, the average bias for unaffiliated analysts is approximately 12%, whereas the average bias for affiliated analysts is approximately 16%. Each of these differences is statistically significant at the 1% level.

In Table 6, Ordinary Least Squares (OLS) is used to estimate the coefficients for the following model using a linear specification for tenure. Standard errors are corrected for hetroskedasticity and clustered at the broker level.

$$BIAS_{it} = \beta_0 + \beta_1 AFF_{it} + \beta_2 TEN_{it} + X' \Gamma_{\mathrm{it}} + \mathrm{Y_t} + \mathrm{I_{it}} + \mathrm{B_i} + \mathrm{e_{it}} \tag{13}$$

AFF_{it} is a dummy variable equal to one if the analyst works for a broker affiliated with the lead manager of the most recent equity issue for the covered firm. TEN_{it} is the number of days since the analyst first appeared in the *I/BE/S* database (divided by 100 for scale). The control variables used for the base specification are number of analysts (*Number of Analysts*), the logarithm of the market capitalization for the covered firm (*Ln*(*Size*)), and the number of days between the analyst's forecast and the report for the firm (*Staleness*). All regressions account for year, industry, and broker fixed effects.

Consistent with the quality of information hypothesis, size has a negative effect on bias. The number of analysts has a positive effect on bias. These coefficients are statistically significant at the 1% level. The point at which an analyst makes his forecast may proxy for the quality of information associated with the forecast. An analyst who makes an early forecast is likely to have lower quality information about the firm when compared to an analyst who makes a forecast shortly before the firm announces earnings. The quality of information factor may also affect bias. In addition, Richardson, Teoh, and Wysocki (2004) show evidence of an "earnings guidance game" between analysts and firm managers; analysts first issue optimistic forecasts and in order to engender beatable targets, they reduce their level of optimism as the firm's earnings announcement date approaches. To control for these factors, I include staleness: a variable for the number of days between the analyst forecast and the firm report. Consistent with the quality of information and "walk-down" hypotheses, staleness has a positive effect on bias when controlling for other variables. The coefficient for staleness is statistically significant at the 1% level.

In Table 6 column (1) revisits the question of whether affiliated analysts are unconditionally more biased than unaffiliated analysts for annual forecasts. For a specification with year, industry, and broker dummies, the coefficient for affiliation is not statistically significant at the 10% level. This is consistent with evidence found in Lin and McNichols (1998).

Table 6 columns (2) and (3) show the results of regressions when using a linear specification for tenure. The result is that bias increases with tenure. For the base specification with year, industry, and broker dummies, the coefficient for tenure is 0.045 and is statistically significant at the 1% level thus rejecting the null for Hypothesis 1. The linear economic effect is that for every 100 days of tenure, analyst bias (expressed in percentage points) is higher by 0.045.

Table 6 column (4) shows the results of a regression where the effect of tenure is allowed to be different based on affiliation status. As predicted by the model, at the start of the career cycle, affiliated analyst bias is less than unaffiliated analyst bias. In addition, the tenure-bias slope for affiliated analysts is greater than the tenure-bias slope for unaffiliated analysts. The coefficient for the affiliation dummy is -3.525 and is statistically significant at the 10% level. The coefficient for tenure is 0.031 and is statistically significant at the 1% level. The coefficient for the interaction term is 0.138 and is statistically significant at the 1% level.

I now relax the linearity assumption and move on to investigate the main hypotheses of the paper using the partial linear regression model with 7^{th} order differencing (See Yatchew (1998) for details on the difference estimator). To investigate the impact of preferential access, I first analyze the data for the pre-Reg FD period (preferential access regime). Figure 1 shows the results for the pre-Reg FD period using the base specification. For unaffiliated analyst and affiliated analyst subsamples, tenure-bias values are estimated using the partial linear regression model. For each subsample, the tenure-bias function is then estimated using local mean smoothing with the bandwidth determined by rule of thumb. I also present 95% confidence interval functions for both subsamples.

For affiliated analysts, the smoothed tenure-bias function is increasing with tenure for most tenure values in the 5^{th}-95^{th} percentile range. This tenure-bias function is clearly not linear for affiliated analysts. The herding hypothesis seems to hold in that for the lowest tenure values, the difference in bias between unaffiliated analysts and affiliated analysts is not statistically significant at the 5% level. As tenure values increase to the 1,000 to 3,000 day range, the difference in bias becomes statistically significant as the effect of herding dissipates; it increases with tenure as predicted by the dynamic moral hazard model. The figure shows that for low tenure values, affiliated bias is estimated to be less than unaffiliated bias. For high tenure values, affiliated bias is estimated to be more than unaffiliated bias. Taken together, the results presented in Figure 1 provide support against the null for Hypothesis 2.

In Figure 3, the dynamics of bias and the interpretation for the relationship between unaffiliated analysts and affiliated analysts is markedly different. That is the predicted relationship between the tenure-bias functions for both types of analysts that is observed in the pre-Reg FD period is not evident in the post-Reg FD period. The figure shows that as predicted by the dynamic moral hazard model, in the absence of preferential access, unaffiliated analysts and affiliated analysts increase bias with tenure at roughly the same rate. In sum, the results reject the null for Hypothesis 3 that there is no impact of regulation on the tenure-bias slope difference.

6. Are Investors Influenced by Conflict of Interest Through Analyst Bias?

Even if analysts are biased, it may be the case that the market adjusts for this behavior. To determine whether the market is influenced by the bias induced by the dynamic incentives of analysts, I use a time-series portfolio regression approach to explain the returns on portfolios sorted on average analyst tenure. Equal-weighted portfolios are formed at the end of each calendar year for the firms in the sample. Monthly excess returns (the return minus the return for the one-month Treasury bill) for these analyst tenure portfolios are regressed on monthly excess market returns (*MktRf*), and factor mimicking portfolios for size (*SMB*), the book equity-market equity ratio (*HML*), momentum (*UMD*), and innovations in liquidity (*LIQ*). Newey-West standard errors are used to adjust for autocorrelation.

Table 3 shows the results of this exercise. I take the difference in returns between Tenure Tercile 1 and Tenure Tercile 3 to capture the returns for a zero-investment portfolio strategy based on analyst tenure. The strategy of buying an equal-weighted portfolio of firms in the lowest analyst tenure tercile and selling an equal-weighted portfolio of firms in the highest analyst tenure tercile earns an abnormal return of approximately 1% per month. The abnormal return coefficient, or alpha, is statistically significant at the 1% level.

7. Robustness

In this section, I investigate the robustness of the results controlling for the misweighting of private information and the under-reaction to public information (prior forecast error, forecast frequency), analyst ability (analyst fixed effects, forecast frequency), analyst effort (forecast frequency), analyst coverage (firm fixed effects), and resource constraints (number of firms followed).

7.1. Analyst Coverage and Tenure

Tenured analysts may not cover the same stocks as untenured analysts (McNichols and O’Brien, 1997). Hence failure to control for analyst coverage is likely to result in false inferences in portfolio regressions and omitted variables bias in forecast bias regressions. To handle this problem, I use firm fixed effects for forecast bias regressions and a sorting procedure for portfolio analysis.

Figure 2 and Figure 3 show the results of forecast bias analysis using firm fixed effects to control for analyst coverage. In Figure 2, unaffiliated analyst bias is less than affiliated analyst bias for low tenure values, whereas affiliated bias is more than unaffiliated bias for high tenure values. In Figure 3, unaffiliated analysts and affiliated analysts increase bias at roughly the same rate. Hence the main results are robust to controlling for analyst coverage using firm fixed effects.

The results in Table 3 suggest that, on average, tenured analysts may not cover the same stocks as untenured analysts. In looking at the Tenure Tercile 1-3 zero-investment portfolio, there appears to be a systematic effect of tenure for two out of the five factor coefficients. The portfolio of firms that are covered by the most tenured analysts has significantly higher *SMB* and *HML* factor coefficients when compared to the portfolio covered by the most untenured analysts.

In Table 4, I double sort stocks perform regression analysis on six portfolios (3 Tenure by 2 Book-to-Market) to control for the types of firms that analysts cover. The main result is that the abnormal return that comes out of the analyst tenure strategy is driven by glamour stocks. This result lends further support to the notion that investors are influenced by analyst bias; it is easier to be influenced with respect to glamour stocks than it is to be influenced with respect to value stocks.

In Table 5, I triple sort stocks and perform regression analysis on 18 portfolios (3 Tenure by 2 Book-to-Market by 3 Size) to further control for analyst coverage. I focus mainly on growth stocks given the result in Table 4. Positive abnormal returns due to the analyst tenure strategy are evident in two of the three size groups (Small-Growth and Large-Growth). This result is robust to using value weights instead of equal weights[9]. Table 5 also shows that there is no difference in the tenure portfolio factor coefficients once I control for book-to-market and size.

7.2. Number of Firms

The number of firms that an analyst covers may have implications for performance. It may be the case that affiliated analysts cover more firms as they gain tenure. These resource constraints may also affect bias. In order to control for this factor, I include a variable for the number of firms covered by the analyst in the year of the report. In the legend in Figure 2, the coefficient for the number of firms when first included is not statistically significant for unaffiliated analysts and affiliated analysts in the pre-Reg FD period. The coefficient for this variable is not statistically significant in the post-Reg FD period for affiliated analysts, but is negative and statistically significant for unaffiliated analysts. The main findings are robust to the inclusion of this variable.

7.3. Forecast Frequency

Forecast frequency may affect bias through the analyst's propensity to use prior information about the covered firm. Forecast frequency may also be a measure of analyst effort (Jacob, Lys,

[9] This result is not reported here, but is available upon request.

and Neale, 1999) and analyst ability (Chen and Jiang, 2006). These three factors may be correlated with analyst tenure. To control for these factors, I include a variable for the average number of forecasts made for a single firm in the year of the report. For both regimes (Figure 2 and Figure 3), the coefficient for forecast frequency when included is positive and statistically significant for unaffiliated analysts, but not statistically significant for affiliated analysts. The main findings are robust to the inclusion of this variable.

7.4. Prior Forecast Error

Given that analyst ability may be persistent, prior forecast error is another variable that is potentially correlated with analyst ability. In addition, prior forecast error may control for analyst under-reaction, which is correlated with analyst tenure (Chen and Jiang, 2006; Mikhail, Walther, and Willis, 2003). Clarke and Subramanian (2006) argue that the level of employment risk is also correlated with prior forecast error, which affects analyst boldness. I control for prior forecast error by including a variable for the average absolute forecast error for the analyst in the year prior to the year of the earnings report.

In the legend in Figure 2, the coefficient for prior forecast error when included is not statistically significant for unaffiliated analysts and affiliated analysts in the pre-Reg FD period. In the legend in Figure 3, the coefficient for prior forecast error when included is positive and statistically significant for both analyst types. The main findings are robust to the inclusion of this variable.

7.5. Analyst Fixed Effects

Time-invariant analyst effects such as innate ability are likely to have an impact on bias (Jacob, Lys, and Neale, 1999) and may be spuriously correlated with tenure. To control for this case, I use a specification with analyst fixed effects. Figure 2 and Figure 3 show that the main results are robust controlling for analyst fixed effects.

8. Conclusion

Analysts certainly have an incentive to be conservative, but the potential for conflict of interest makes bias attractive. Financial analysts potentially face two sources of conflict of interest: brokerage trading commissions and possibly underwriter affiliation. Over the course of an analyst's career, the temptation to yield to these conflicts grows as his motivation for developing a reputation of accuracy wanes. Potentially conflicted analysts increase bias with tenure as a result of this dynamic tradeoff.

This dynamic tradeoff is affected by privileged access, which is modeled in this paper in the form of an employer information hierarchy. The precision with which employers evaluate analysts increases with privileged access. Analysts gain privileged access to the managers of covered firms through underwriter affiliation (Allen and Faulhaber, 1989).

Early in the career cycle, affiliated analysts are more conservative than unaffiliated analysts because of significant wage benefits going forward, and moving to an employer with no privileged access early in the career cycle would entail little to no wage premium for the affiliated analyst. Late periods enable the affiliated analyst to benefit from his privileged position. Having established a good reputation, the affiliated analyst has less of an incentive to be accurate, compared to the incentive for an unaffiliated analyst who has not had the benefit of privileged access. Therefore in late periods affiliated analysts are more optimistic than unaffiliated analysts.

Annual analyst earnings forecast bias increases with tenure. Investors are influenced by the dynamic nature of analyst bias. A portfolio strategy using analyst tenure earns an abnormal return of approximately 1% per month for growth stocks. This result suggests that for opaque firms, investors do not adjust their expectations downward in the presence of analyst bias.

In the pre-Reg FD period, affiliated analyst bias is less than unaffiliated analyst bias for low tenure values. The difference in bias between affiliated analysts and unaffiliated analysts increases over time. In the post-Reg FD period, both analyst types increase bias with tenure at roughly the same rate. These results provide support for the proposed model.

This study offers three immediate takeaways. First, privileged access has a dynamic effect on career outcomes. Second, dynamic learning significantly informs analyst behavior, and conclusions based on static differences can be misleading. Third, analyst bias has a significant impact on asset prices[10].

Consider a deeper analysis of the results from the pre-Reg FD period. One may be skeptical of the proposed effect of privileged access, simply assuming instead that affiliated analysts enjoy

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[10] The evidence presented in this paper becomes especially striking when reviewed alongside the finding that individual investors are even more susceptible to recommendation bias (Malmendier and Shanthikumar, 2007a, 2007b).

a greater compensation factor through potential conflict of interest, or that affiliated analysts misweight information more than unaffiliated analysts. While these factors play a role, they constitute only part of the story. These factors do not go all the way to further our understanding of the obvious pattern in the data, failing to explain why affiliated analyst bias is lower than unaffiliated analyst bias for low tenure values, or why the two tenure-bias functions intersect in the middle of the tenure range[11]. More importantly, it cannot explain the effect of Reg FD. In the post-Reg FD period, both analyst types increase bias with tenure at roughly the same rate, which is in sharp contrast with the dynamics of the pre-Reg FD period.

The asset pricing results presented here suggest that market efficiency may be adversely affected by analyst bias, which is largely driven by potential conflict of interest. As Mehran and Stulz (2007) suggest, conflict of interest is more of a problem when markets are influenced by bias. Given that both analyst types increase bias with tenure at roughly the same rate, the paper provides support for the relative importance of potential conflict of interest through trading commissions when compared to investment banking affiliation[12]. Policymakers should therefore continue to strengthen rules that promote equal access and seriously consider enacting new rules that limit the incentive effect that trading commissions have on financial analysts.

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[11] In addition, Clarke et al. (2007) show that high-ability analysts do not change their level of bias when moving from an unaffiliated broker to an affiliated broker.

[12] Cowen, Groysberg, and Healy (2006) use data on different types of analyst employers to show that trading commission incentives are more important than investment bank incentives with respect to forecast bias.

Future research on financial analysts should continue to incorporate the important role of dynamic learning and its effects. Herding is a byproduct of dynamic learning, and its interaction with the information hierarchy merits further study. Still another fruitful area of research would be the effect of dynamic incentives on other types of analyst forecasts: growth, long term forecasts, and quarterly forecasts.

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Table 1. Privileged Access and Analyst Career Concerns: Sample Statistics

The table provides sample statistics for annual analyst forecasts in the sample. Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. The sample period is from January 1993 to December 2005. *Affiliated* is a dummy variable equal to one if the analyst is employed by a brokerage affiliated with the lead manager for the most recent issue of the covered firm. *Size* is the sample period average of the market capitalization for the covered firm (in millions of US dollars). *Number of Analysts* is the number of analysts who cover the firm in the year of the report. *Tenure* is the number of days since the analyst's first forecast in the I/B/E/S database (divided by 100 for scale). *Tenured* is a dummy variable equal to one if *Tenure* is greater than the median value of tenure for the sample. *Number of Firms* is the number of firms covered by the analyst in the year of the report. *Forecast Frequency* is the average number of forecasts made for a single firm by the analyst in the year of the report. *Staleness* is the number of days that the analyst's forecast exists before the firm's report is released. *, **, *** denote statistical significance at the 10%, 5% and 1% levels.

Panel A

Variable Name		**Affiliated**	**Unaffiliated**	**Difference**	**All**
Size (in $MM)	Mean	7689.353	12207.830	4518.480***	11783.130
	se.	241.963	101.735	325.329	95.033
	N	8967	86434	95401	95401
Number of Analysts	Mean	12.813	17.192	- 4.378***	16.780
	se.	0.082	0.028	0.090	0.027
	N	8967	86434	95401	95401
Tenure	Mean	29.373	25.062	4.311***	25.467
	se.	0.200	0.064	0.207	0.061
	N	8967	86434	95401	95401
Number of Firms	Mean	15.531	13.982	1.549***	14.128
	se.	0.081	0.031	0.099	0.029
	N	8967	86434	95401	95401
Forecast Frequency	Mean	4.037	4.094	- 0.057***	4.089
	se.	0.016	0.006	0.019	0.006
	N	8967	86434	95401	95401
Staleness	Mean	197.903	198.490	- 0.587	198.435
	se.	1.087	0.350	1.142	0.333
	N	8967	86434	95401	95401

Panel B

Variable Name		Tenured	Untenured	Difference	All
Size (in $MM)	Mean	11758.080	11808.150	50.071	11783.130
	se.	133.925	134.866	190.066	95.033
	N	47682	47719	95401	95401
Number of Analysts	Mean	16.379	17.182	- 0.803***	16.780
	se.	0.036	0.039	0.053	0.027
	N	47682	47719	95401	95401
Affiliated	Mean	0.112	0.076	0.036***	0.094
	se.	0.001	0.001	0.002	0.001
	N	47682	47719	95401	95401
Number of Firms	Mean	16.631	11.626	5.005***	14.128
	se.	0.043	0.035	0.056	0.029
	N	47682	47719	95401	95401
Forecast Frequency	Mean	4.155	4.023	0.132***	4.089
	se.	0.008	0.008	0.011	0.006
	N	47682	47719	95401	95401
Staleness	Mean	197.738	199.132	- 1.394**	198.435
	se.	0.472	0.470	0.666	0.333
	N	47682	47719	95401	95401

Table 2. Privileged Access and Analyst Career Concerns: Univariate Analysis by Tenure Tercile and Underwriter Affiliation

The table provides sample statistics for the percentage bias associated with annual analyst forecasts in the sample along with positive-negative odds and positive group odds ratios for bias. Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. The sample period is from January 1993 to December 2005. *Odds* is the ratio of positive values to negative values. *Odds Ratio* is the ratio of odds for affiliated analysts to the odds for unaffiliated analysts. *Bias* is the difference between the earnings forecast and the actual earnings figure, expressed as a percentage of the firm's actual earnings. *Affiliated* is a dummy variable equal to one if the analyst is employed by a firm affiliated with the lead manager for the most recent issue of the covered firm. *Tenure* is the number of days since the analyst's first forecast in the I/B/E/S database (divided by 100 for scale). *Tenure Tercile 1* represents the group with the lowest tenure values. *Tenure Tercile3* represents the group with the highest tenure values. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively, in a two-sided test with the null hypothesis that the mean is equal to zero.

Panel A

	AFFILIATED		**UNAFFILIATED**			**ALL**	
Tenure Tercile	**Bias**	**Odds**	**Bias**	**Odds**	**Odds Ratio**	**Bias**	**Odds**
1	8.051***	0.753	11.819***	0.889	0.848	11.575***	0.879
2	9.159***	0.853	10.578***	0.853	1.000	10.423***	0.853
3	16.278***	1.074	12.152***	0.953	1.126	12.607***	0.966

Panel B

	(1) AFFILIATED	**(2) UNAFFILIATED**	**(1) – (2)**
Tenure Tercile	**Bias**	**Bias**	**Difference in Bias**
1	8.051	11.819	-3.768***
2	9.159	10.578	-1.419**
3	16.278	12.152	4.126***

Table 3. Analyst Career Concerns: The Impact on Asset Prices

The table presents the results of time series portfolio regression analysis for January 1995 to December 2005 where the dependent variable is the monthly portfolio return in excess of the risk-free rate. Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. Firms in the sample are sorted at the end of each calendar year into three terciles based on the average tenure of the analysts covering the firm. Tercile portfolios are subsequently formed on January 1st each year and are equal-weighted monthly. Portfolios with coverage by the lowest tenure analysts are in *Tenure Tercile 1* and portfolios with coverage the highest tenure analysts are in *Tenure Tercile 3*. *MktRf* is the monthly return on the market index in excess of the risk-free rate. *SMB* is the monthly return on a factor mimicking portfolio for firm size. *HML* is the monthly return on a factor mimicking portfolio for firm book-to-market equity. *UMD* is the monthly return on a factor mimicking portfolio for momentum. *LIQ* is the factor for innovations in liquidity (Pastor and Stambaugh (2003)). *Alpha* is the intercept for each regression. The Model *p*-value shows the result for a test that all of the listed coefficients are jointly zero. *, **, *** denote statistical significance at the 10%, 5% and 1% levels. Newey-West standard errors with three lags are used to adjust for autocorrelation.

Tenure Tercile	(1)	(2)	(3)	(1) – (3)
Alpha	0.879***	0.494*	0.253	0.946***
	(0.239)	(0.267)	(0.226)	(0.287)
MktRf	1.046***	1.046***	1.054***	-0.006
	(0.071)	(0.066)	(0.056)	(0.068)
SMB	0.786***	0.812***	0.941***	-0.161**
	(0.066)	(0.092)	(0.065)	(0.068)
HML	0.046	0.058	0.278***	-0.234**
	(0.076)	(0.094)	(0.075)	(0.094)
UMD	-0.310***	-0.273***	-0.231***	-0.077
	(0.072)	(0.057)	(0.041)	(0.056)
LIQ	-0.039	0.018	0.019	-0.058
	(0.040)	(0.044)	(0.034)	(0.047)
Number of Months	156	156	156	156
p-value	0.000	0.000	0.000	0.000

Table 4. Analyst Career Concerns: Analyst Tenure and Glamour Stocks

The table presents the results of time series portfolio regression analysis for January 1995 to December 2005 where the dependent variable is the monthly portfolio return in excess of the risk-free rate. Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. Firms in the sample are sorted at the end of each calendar year into six portfolios (three terciles based on the average tenure of the analysts covering the firm and two groups for each tercile based on the median book-to-market cutoff for the previous year). Portfolios are formed on January 1st each year and are equal-weighted monthly. I report results for portfolios with coverage by the lowest tenure analysts (*Tenure Tercile 1)* and portfolios with coverage by the highest tenure analysts (*Tenure Tercile 3)*. Columns (5) and (6) provide results for zero-investment analyst tenure portfolios for growth and value stocks. *MktRf* is the monthly return on the market index in excess of the risk-free rate. *SMB* is the monthly return on a factor mimicking portfolio for firm size. *HML* is the monthly return on a factor mimicking portfolio for firm book-to-market equity. *UMD* is the monthly return on a factor mimicking portfolio for momentum. *LIQ* is the factor for innovations in liquidity (Pastor and Stambaugh (2003)). *Alpha* is the intercept for each regression. The Model *p*-value shows the result for a test that all of the listed coefficients are jointly zero. *, **, *** denote statistical significance at the 10%, 5% and 1% levels. Newey-West standard errors with three lags are used to adjust for autocorrelation.

Portfolio	(1)	(2)	(3)	(4)	(1) – (3)	(2) – (4)
Tenure	(1)	(1)	(3)	(3)		
Book-to-Market	(1)	(2)	(1)	(2)		
Alpha	1.054***	1.459*	0.013	0.275	1.041***	1.184
	(0.255)	(0.814)	(0.259)	(0.420)	(0.351)	(0.932)
MktRf	1.051***	1.107***	1.065***	1.090***	-0.013	0.017
	(0.076)	(0.187)	(0.069)	(0.124)	(0.088)	(0.236)
SMB	0.738***	0.784***	0.886***	1.021***	-0.148*	-0.237
	(0.063)	(0.264)	(0.079)	(0.174)	(0.089)	(0.351)
HML	0.100	-0.086	0.335***	0.068	-0.235*	-0.154
	(0.086)	(0.215)	(0.092)	(0.168)	(0.138)	(0.262)
UMD	-0.292***	-0.828**	-0.224***	0.015	-0.068	-0.843**
	(0.068)	(0.362)	(0.037)	(0.094)	(0.077)	(0.390)
LIQ	-0.040	-0.135	0.023	0.087	-0.063	-0.222
	(0.042)	(0.121)	(0.048)	(0.107)	(0.053)	(0.156)
Number of Months	156	156	156	156	156	156
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Table 5. Analyst Career Concerns: Analyst Tenure and Glamour Stocks Controlling for Size

The table presents the results of time series portfolio regression analysis for January 1995 to December 2005 where the dependent variable is the monthly portfolio return in excess of the risk-free rate. Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. Firms in the sample are sorted at the end of each calendar year into 18 portfolios (three terciles based on the average tenure of the analysts covering the firm, two groups for each tercile based on the median book-to-market cutoff for the previous year, and three terciles for each double-sorted portfolio based on tercile size cutoffs for the previous year). Portfolios are formed on January 1st each year and are equal-weighted monthly. I report results for portfolios with coverage by the lowest tenure analysts (*Tenure Tercile 1)* and portfolios with coverage by the highest tenure analysts (*Tenure Tercile 3)*. Columns (7), (8) and (9) provide results for zero-investment analyst tenure portfolios for small-growth, mid-growth and large-growth stocks. Table 3 gives the definition for each factor in the model. *Alpha* is the intercept for each regression. The Model *p*-value shows the result for a test that all of the listed coefficients are jointly zero. *, **, *** denote statistical significance at the 10%, 5% and 1% levels. Newey-West standard errors with three lags are used to adjust for autocorrelation.

Portfolio	(1)	(2)	(3)	(4)	(5)	(6)	(1) – (4)	(2) – (5)	(3) – (6)
Tenure	(1)	(1)	(1)	(3)	(3)	(3)			
Book-to-Market	(1)	(1)	(1)	(1)	(1)	(1)			
Size	(1)	(2)	(3)	(1)	(2)	(3)			
Alpha	1.519***	0.795**	1.171***	1.307	2.030***	0.704	2.876**	0.049	1.898**
	(0.525)	(0.390)	(0.424)	(1.615)	(0.713)	(0.798)	(1.249)	(1.217)	(0.896)
MktRf	0.976***	1.062***	1.091***	1.384***	0.936***	0.814***	-0.409	0.319	0.129
	(0.110)	(0.133)	(0.111)	(0.279)	(0.286)	(0.182)	(0.268)	(0.463)	(0.245)
SMB	0.789***	0.685***	0.576***	0.363	0.588*	1.661***	0.057	0.287	0.528
	(0.144)	(0.144)	(0.117)	(0.395)	(0.312)	(0.272)	(0.392)	(0.434)	(0.418)
HML	0.345*	0.097	0.091	0.548*	0.601**	0.097	-0.656	0.211	0.321
	(0.188)	(0.152)	(0.127)	(0.293)	(0.296)	(0.299)	(0.545)	(0.335)	(0.440)
UMD	-0.406**	-0.265***	-0.277***	-0.556***	-0.707***	-0.052	-0.100	-0.434**	0.142
	(0.168)	(0.090)	(0.062)	(0.194)	(0.173)	(0.116)	(0.475)	(0.200)	(0.280)
LIQ	-0.008	-0.148**	0.017	-0.050	0.054	-0.020	-0.112	-0.510*	0.074
	(0.082)	(0.067)	(0.082)	(0.171)	(0.127)	(0.140)	(0.196)	(0.295)	(0.213)
Number of Months	156	156	156	156	156	156	156	156	156
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

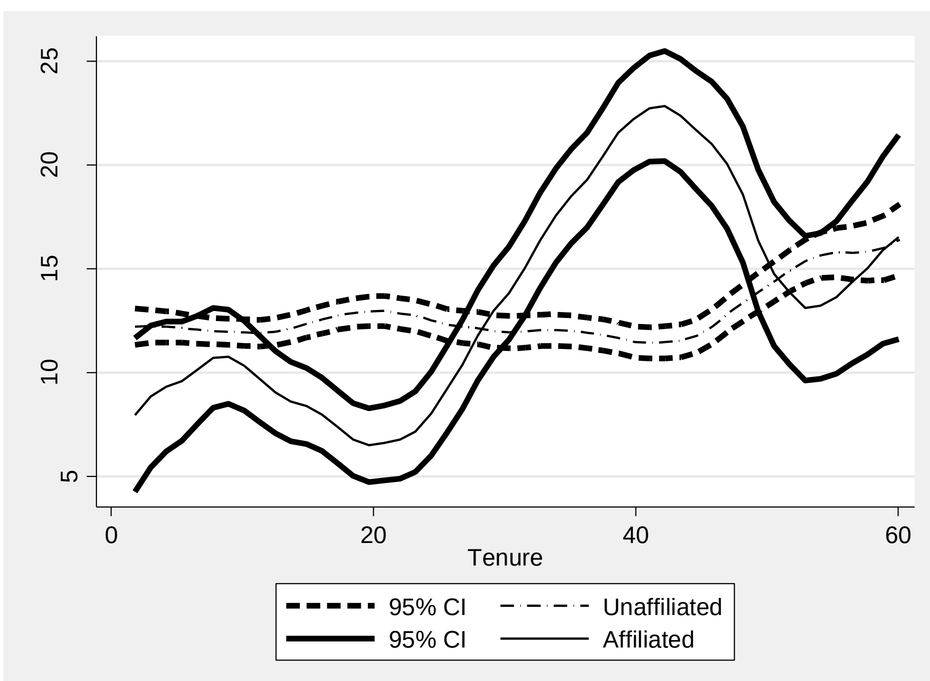
Table 6. Privileged Access and Analyst Career Concerns: Linear Regression Analysis

The table presents the results of regression analysis using ordinary least squares (OLS) where the dependent variable is *Bias.* The sample period is from January 1993 to December 2005. Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. *Bias* is the difference between the earnings forecast and the actual earnings figure, expressed as a percentage of the firm's actual earnings. *Tenure* is the number of days since the analyst's first forecast in the I/B/E/S database (divided by 100 for scale). *Ln(Size)* is the logarithm of the sample period average of the market capitalization for the covered firm. *Number of Analysts* is the number of analysts who cover the firm in the year of the report. *Staleness* is the number of days that the analyst's forecast exists before the firm's report is released. *Affiliated* is a dummy variable equal to one if the analyst is employed by a firm affiliated with the lead manager for the most recent issue of the covered firm. Heteroscedasticity-robust standards errors, corrected for clustering at the broker level, are in parentheses. The Model *p*-value shows the result for a test that all of the listed coefficients are jointly zero. *, **, *** denote statistical significance at the 10%, 5% and 1% levels.

Ln(Size)	-5.269	-5.321	-5.322	-5.326
	(0.208)***	(0.208)***	(0.209)***	(0.210)***
Number of Analysts	0.441	0.446	0.446	0.447
	(0.043)***	(0.044)***	(0.043)***	(0.043)***
Staleness	0.069	0.069	0.069	0.069
	(0.002)***	(0.002)***	(0.002)***	(0.002)***
Affiliated	-0.032		-0.058	-3.525
	(2.163)		(2.156)	(2.121)*
Tenure		0.045	0.045	0.031
		(0.017)***	(0.017)***	(0.013)***
Affiliated * Tenure				0.138
				(0.033)***
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
Broker Dummies	Yes	Yes	Yes	Yes
Number of Observations	95401	95401	95401	95401
Model *p*-value	0.000	0.000	0.000	0.000

Figure 1. Privileged Access and Analyst Career Concerns: Pre-Regulation Fair Disclosure

The figure presents *Bias* as flexible functions of tenure controlling for *Ln(Size), Number of Analysts,* and *Staleness.* The sample period is from January 1993 to October 23, 2000 (the effective implementation date for Regulation Fair Disclosure). Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. *Bias* is the difference between the earnings forecast and the actual earnings figure, expressed as a percentage of the firm's actual earnings. *Ln(Size)* is the logarithm of the sample period average of the market capitalization for the covered firm. *Number of Analysts* is the number of analysts who cover the firm in the year of the report. *Staleness* is the number of days that the analyst's forecast exists before the firm's report is released. *Tenure* is the number of days since the analyst's first forecast in the I/B/E/S database (divided by 100 for scale). Tenure values are between the 5th and 95th percentiles. Tenure-bias values are estimated using a partial linear (PL) regression model with 7th order differencing and smoothed using local mean smoothing with a rule of thumb bandwidth. There is one function for each group based on affiliation status. *Affiliated* is a dummy variable equal to one if the analyst is employed by a firm affiliated with the lead manager for the most recent issue of the covered firm. The Model *p*-value shows the result for a test that all of the listed coefficients are jointly zero. *, **, *** denote statistical significance at the 10%, 5% and 1% levels.

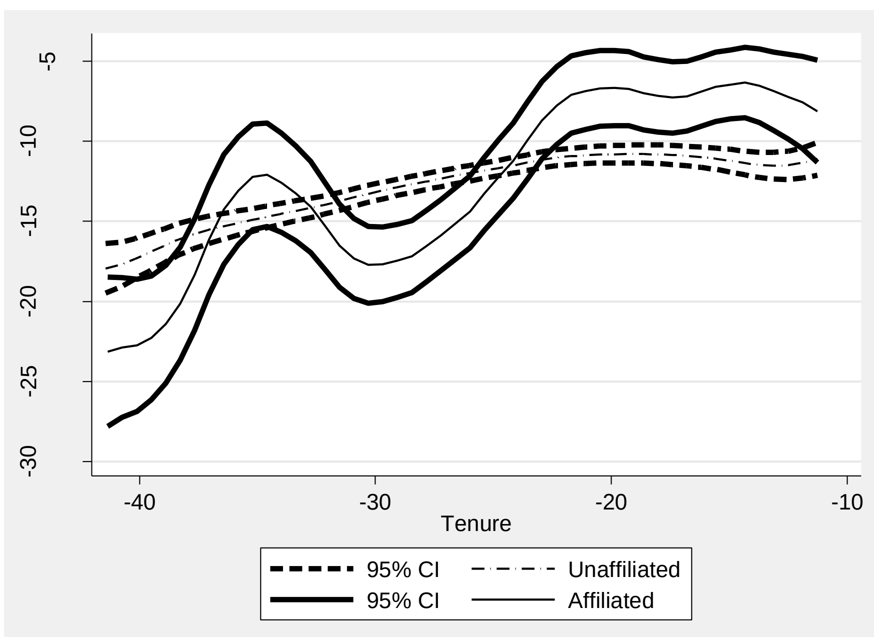


Legend

	UNAFFILIATED	AFFILIATED
Ln(Size)	-7.848 (0.166)***	-8.021 (0.505)***
Number of Analysts	0.976 (0.031)***	0.793 (0.099)***
Staleness	0.073 (0.002)***	0.070 (0.005)***
Year Dummies	Yes	Yes
Industry Dummies	Yes	Yes
Broker Dummies	Yes	Yes
Number of Observations	50688	5546
Model *p*-value	0.000	0.000

Figure 2. Privileged Access and Analyst Career Concerns: Robust Specification for Pre-Regulation Fair Disclosure

The figure presents *Bias* as flexible functions of tenure for controlling for *Ln(Size), Number of Analysts, Staleness, Number of Firms, Forecast Frequency,* and *Prior Error.* The sample period is from January 1994 to October 23, 2000 (the effective implementation date for Regulation Fair Disclosure). Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. *Bias* is the difference between the earnings forecast and the actual earnings figure, expressed as a percentage of the firm's actual earnings. *Tenure* is the number of days since the analyst's first forecast in the I/B/E/S database (divided by 100 for scale). Tenure values are between the 5th and 95th percentiles. Tenure-bias values are estimated using a partial linear (PL) regression model with 7th order differencing and smoothed using local mean smoothing with a rule of thumb bandwidth. There is one function for each group based on affiliation status. *Affiliated* is a dummy variable equal to one if the analyst is employed by a firm affiliated with the lead manager for the most recent issue of the covered firm. The base specification includes *Ln(Size), Number of Analysts,* and *Staleness.* Base specification variables are defined in Table 6. *Number of Firms* is the number of firms covered by the analyst in the year of the report. *Forecast Frequency* is the average number of forecasts made for a single firm by the analyst in the year of the report. *Prior Error* is the mean forecast error for the analyst in the year prior to the year of the report. All variables are demeaned for firm fixed effects and analyst fixed effects The Model *p*-value shows the result for a test that all of the listed coefficients are jointly zero. *, **, *** denote statistical significance at the 10%, 5% and 1% levels.

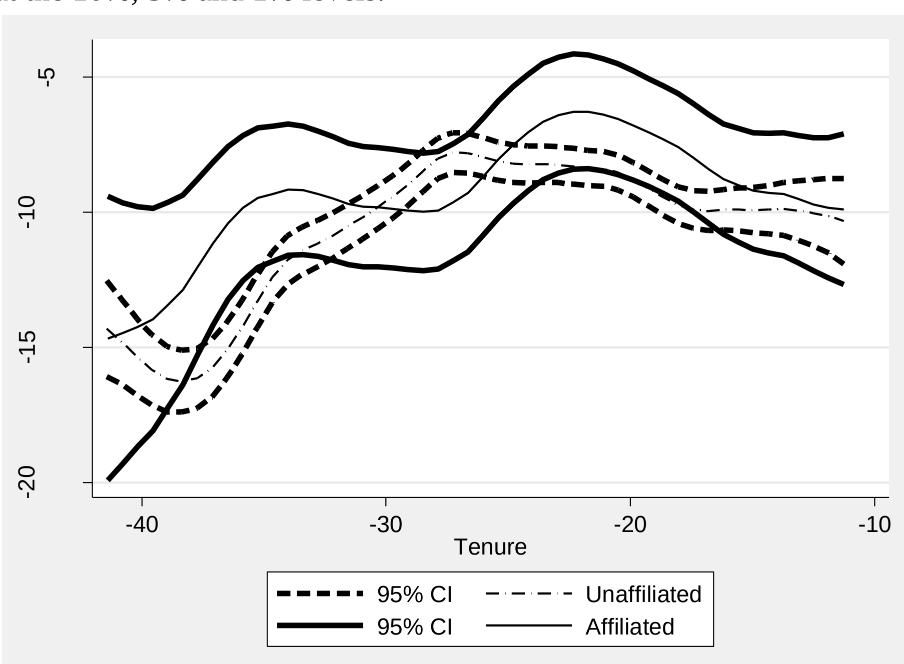


Legend

	UNAFFILIATED	AFFILIATED
Ln(Size)	-7.524	-6.349
	(0.273)***	(0.890)***
Number of Analysts	0.895	0.647
	(0.043)***	(0.145)***
Staleness	0.077	0.073
	(0.002)***	(0.005)***
Number of Firms	0.064	0.172
	(0.040)	(0.116)
Forecast Frequency	0.972	0.493
	(0.194)***	(0.499)
Prior Error	-0.056	-0.210
	(0.314)	(0.369)
Year Dummies	Yes	Yes
Industry Dummies	Yes	Yes
Broker Dummies	Yes	Yes
Firm Fixed Effects	Yes	Yes
Analyst Fixed Effects	Yes	Yes
Number of Observations	41614	4680
Model *p*-value	0.000	0.000

Figure 3. Analyst Career Concerns: Robust Specification for Post-Regulation Fair Disclosure

The figure presents *Bias* as flexible functions of tenure for controlling for *Ln(Size), Number of Analysts, Staleness, Number of Firms, Forecast Frequency,* and *Prior Error.* The sample period is from October 23, 2000 (the effective implementation date for Regulation Fair Disclosure) to December 2005. Sample construction requires that for a given year, there be at least one affiliated analyst and at least one unaffiliated analyst covering the firm. *Bias* is the difference between the earnings forecast and the actual earnings figure, expressed as a percentage of the firm's actual earnings. *Tenure* is the number of days since the analyst's first forecast in the I/B/E/S database (divided by 100 for scale). Tenure values are between the 5th and 95th percentiles. Tenure-bias values are estimated using a partial linear (PL) regression model with 7th order differencing and smoothed using local mean smoothing with a rule of thumb bandwidth. There is one function for each group based on affiliation status. *Affiliated* is a dummy variable equal to one if the analyst is employed by a firm affiliated with the lead manager for the most recent issue of the covered firm. The base specification includes *Ln(Size), Number of Analysts,* and *Staleness.* Base specification variables are defined in Table 6. *Number of Firms* is the number of firms covered by the analyst in the year of the report. *Forecast Frequency* is the average number of forecasts made for a single firm by the analyst in the year of the report. *Prior Error* is the mean forecast error for the analyst in the year prior to the year of the report. All variables are demeaned for firm fixed effects and analyst fixed effects The Model *p*-value shows the result for a test that all of the listed coefficients are jointly zero. *, **, *** denote statistical significance at the 10%, 5% and 1% levels.



Legend

	UNAFFILIATED	AFFILIATED
Ln(Size)	-3.140	-4.059
	(0.305)***	(0.972)***
Number of Analysts	0.275	0.423
	(0.050)***	(0.178)*
Staleness	0.070	0.072
	(0.002)***	(0.006)***
Number of Firms	-0.197	0.232
	(0.060)**	(0.135)
Forecast Frequency	0.704	0.596
	(0.154)***	(0.584)
Prior Error	0.599	6.817
	(0.089)***	(1.729)***
Year Dummies	Yes	Yes
Industry Dummies	Yes	Yes
Broker Dummies	Yes	Yes
Firm Fixed Effects	Yes	Yes
Analyst Fixed Effects	Yes	Yes
Number of Observations	32532	3134
Model *p*-value	0.000	0.000

Appendix

The Model

No Information Hierarchy

The model without an information hierarchy is a variant of Holmstrom (1999). Consider the following three-period model of a competitive labor market for a financial analyst. I assume that the analyst is endowed with labor that he uses to make forecasts about future firm earnings. No contingent contracts can be made; the analyst is paid for his services in advance. The earnings amount that the firm reports to the market is X_{rt}. Ex-ante, this amount is not known to the analyst or the market. In each period, the analyst produces a forecast $\widehat{X_t}$ of firm earnings. The analyst is compensated for his ability by the market. The market infers ability by observing ex-post squared forecast error, v_t.

$$v_t = \left(\widehat{X_t} - X_{rt}\right)^2 \tag{1}$$

Assume that the analyst observes a noisy signal $S_t = X_{rt} + e_t(\theta)$, where noise is a function of innate ability θ. A high ability analyst is better than a low ability analyst when it comes to predicting the reported value of the firm.

In period t, the conditional expected squared forecast error is a function of ex-ante bias, b_t; $b_t \in [b_{min}, b_{max}]$, and the conditional variance of the earnings report. In turn, the analyst's prediction of the variance of the earnings report is a function of ability.

$$b_t = \widehat{X_t} - E[X_{rt} | S_t] \tag{2}$$

$$E[\,v_t|S_t] = {b_t}^2 + Var[X_{rt}|S_t] = {b_t}^2 + Var[X_{rt}] - \theta \quad (3)$$

It follows that the ex-post squared forecast error that the market uses in order to infer analyst ability can be represented in the following manner.

$$\nu_t = {b_t}^2 - \theta + \varepsilon_t, \qquad t = 1,2,3 \quad (4)$$

where ε_t is a noise parameter with mean equal to $Var[X_{rt}]$. In addition to being explicitly rewarded for low error, the analyst receives a benefit for producing a biased forecast. This non-contractible benefit $\psi'(b_t)$, is an increasing linear function of b_t; $\psi'(b_t) > 0$ and $\psi''(b_t) = 0$. It can be interpreted as a potential conflict of interest term.

The analyst's risk neutral preferences can be represented by the following atemporal, separable utility function.

$$U(c) = \sum_{t=1}^{3} \delta^{t-1} c_t, \quad (5)$$

where c_t represents consumption in period t and the functional form of $U(c)$ is public knowledge. Note that the analyst effectively chooses bias. Due to the nature of bias, the employer does not observe this value ex-ante. In order to decide on the extent to which he will be biased, the analyst calculates the effect that bias has on future wages. The analyst's decision rule and the wage functions are determined simultaneously in equilibrium.

$v^t = (v_1,.., v_t)$ is the sequence of past values of squared forecast error up to time t. This sequence is known to the market. It is assumed that the employer uses this as a basis for wages. Let $w_t(v^{t-1})$ be the wage in period t and $b_t(v^{t-1})$ be the bias that the analyst chooses in the same period. Given the analyst's decision rule, the employer sets wages in a risk neutral labor market according to the following equation

$$w_t(\nu^{t-1}) = K - E[\,\nu_t|\nu^{t-1}] = K - b_t(\nu^{t-1})^2 + E[\theta|\nu^{t-1}], \tag{6}$$

where *K* is a constant to ensure a strictly positive wage in the market. Given (6), the analyst's decision rule solves

$$\max_{\{b_t(.)\}} \sum_{t=1}^{3} \delta^{t-1}\left[Ew_t(\nu^{t-1}) + E\psi\big(b_t(\nu^{t-1})\big)\right] \tag{7}$$

The solution to (7) together with (6) determines equilibrium.

Given that ex-ante bias is chosen based on the analyst's forecast of firm earnings, it is not observable by the employer. Employers though, can infer the analyst's actions through solving the analyst's decision rule. The employers use the following sequence $\{u_t\}$ to learn about θ.

$$u_t \equiv \theta + \varepsilon_t = b_t^{*2} - v_t\ , \tag{8}$$

where b_t^* represents the equilibrium decision rule for the analyst.

The employer and the analyst share prior beliefs about θ. Assume that the prior is normally distributed with mean m_1 and precision (the inverse of the variance) h_1. Dynamic learning about θ occurs through the observation of the analyst's ex-post squared forecast error. The posterior distribution for θ is normal with the following updated parameters.

$$\mathrm{m}_{t+1} = \frac{h_t m_t + h_\varepsilon u_t}{h_{t+1}} \tag{9}$$

$$h_{t+1} = h_t + h_\varepsilon \tag{10}$$

Let us now solve for the three-period model. For $t \in \{2, 3\}$, the analyst's wage in period t is determined by the quality of the forecast given in period *t-1*. The analyst does not suffer a reputational cost from being biased in period three. Hence all analysts make forecasts using the maximum amount of bias in the final period.

In period two, the analyst chooses b_2 to maximize the following payoff.

$$w_2(\nu^1) + \psi\big(b_2(\nu^1)\big) + \delta\big[Ew_3(\nu^2) + E\psi\big(b_3(\nu^2)\big)\big] \tag{11}$$

Through market incentives, the analyst is induced to minimize bias. Hence the equilibrium condition for b_2 is as follows.

$$b_2^* = \frac{\psi^{'}(b_2^*)}{2\delta\alpha_3} \quad \text{, where} \tag{12}$$

$$\alpha_t = \frac{h_\varepsilon}{h_t} \tag{13}$$

In period one, the analyst chooses b_1 to maximize the following payoff.

$$w_1 + \psi(b_1) + \delta\big[Ew_2(\nu^1) + E\psi\big(b_2(\nu^1)\big)\big] + \delta^2\big[Ew_3(\nu^2) + E\psi\big(b_3(\nu^2)\big)\big] \tag{14}$$

This maximization problem results in the following equilibrium condition for b_1.

$$b_1^* = \frac{\psi^{'}(b_1^*)}{2(\delta\alpha_2 + \delta^2\alpha_3)} \tag{15}$$

Proposition A.1 (Dynamic Incentives and Analyst Bias) *In the absence of an information hierarchy, financial analysts increase bias with tenure.*

Proof of Proposition A.1

Since $\psi^{'}(b_1^*) = \psi^{'}(b_2^*)$, $b_1^* < b_2^*$ follows from the fact that $2(\delta\alpha_2 + \delta^2\alpha_3) > 2\delta\alpha_3$ ■

Proposition A.1 shows that analysts become more biased with tenure. This is akin to the familiar result that implicit market incentives induce workers to exert effort in early periods more so than in late periods (Holmstrom (1999)). While the familiar labor market result occurs through the output-effort tradeoff, the result in Proposition A.1 occurs through the tradeoff between the reputation building benefits of low error and the non-contractible benefits of bias.

Information Hierarchy

There are now two types of employers in this market, indexed by type $j \in \{A, U\}$. The analyst is randomly assigned an employer type in the initial period. Employer *A* hires the analyst to make forecasts about firms with which Employer *A* has a privileged relationship. Employer *U* hires the analyst to make forecasts about firms with which Employer *U* does not have a privileged relationship. Initially, the analyst is hired to work with one type of employer, but may move between employer types over the course of his career.

Analyst ability now has two components: η and τ, where $\theta = \eta + \tau$. The first component, η, is the ability of the analyst to process public information about future firm performance. The second component, τ, is the ability of the analyst to acquire and process private information about future firm performance.

Employer *A* has information about τ that he uses, in addition to $v_{t,}$ in order to infer θ, but only if the analyst was most recently employed by Employer *A*. Hence Employer *A* has information rights on τ. Employer *U* is only able to infer θ through v_t irrespective of previous employers. Formally, Employer *U* observes the distribution of θ with precision $h_{U\varepsilon}$ irrespective of previous employers. Employer *A* though, observes the distribution of θ with precision $h_{A\varepsilon}$ only if the analyst was most recently employed by Employer *A*. If the analyst was most recently employed by Employer U, then Employer A observes the distribution of θ with precision $h_{U\varepsilon}$. I assume $h_{A\varepsilon} > h_1 > h_{U\varepsilon}$.

The probability that the analyst works for Employer A in period t is $P_t(v^{t-1})$. Employer A selects analysts based on ex-post squared forecast error and Employer U has no power to select analysts; the analysts who do not work for Employer A simply work for Employer U. Finally, I assume that there is an exclusivity condition; in equilibrium, analysts are selected so that $P_t(v^{t-1}) = P$. This condition can be interpreted as a limit on the size of the privileged analyst labor force.

Let $j^t = (j_1,.., j_t)$ be the sequence of employers for the analyst. This sequence is known to the market. It is assumed that both types of employers use this as a basis for wages. Given the analyst's decision rule, each employer sets wages in a risk neutral labor market according to the following equation

$$w_t(\nu^{t-1}, j^{t-1}) = K - E[\,\nu_t|\nu^{t-1}, j^{t-1}] = K - b_t(\nu^{t-1}, j^{t-1})^2 + E[\theta|\nu^{t-1}, j^{t-1}], \tag{16}$$

where K is a constant to ensure a strictly positive wage in the market. Given (16), the analyst's decision rule solves

$$\max_{\{b_t(.)\}} \sum_{t=1}^{3} \delta^{t-1}\left[E w_t(\nu^{t-1}, j^{t-1}) + E\psi\big(b_t(\nu^{t-1}, j^{t-1})\big)\right] \tag{17}$$

The solution to (17) together with (16) determines equilibrium. Note that even though the labor market is competitive within employer types, the wage that the analyst earns depends on his employer path.

Both types of employers and the analyst share prior beliefs about θ. The posterior distribution for θ is normal with the following updated parameters[13].

$$\mathrm{m}_{t+1}(j^{t+1}) = \frac{h_t(j^t)m_t(j^t)+h_\varepsilon(j^{t+1})u_t}{h_{t+1}(j^{t+1})} \tag{18}$$

$$h_{t+1}(j^{t+1}) = h_t(j^t) + h_\varepsilon(j^{t+1}) \tag{19}$$

Let us now solve for the three-period model with an information hierarchy. For $t \in \{2, 3\}$, the analyst's wage in period t is determined by the quality of the forecast given in period t-*1*. The analyst does not suffer a reputational cost from being biased in period three. Hence, irrespective of the employer, all analysts make forecasts using the maximum amount of bias in the final period.

In period two, the analyst chooses b_2 to maximize the following payoff

$$w_2(\nu^1, j^1) + \psi\big(b_2(\nu^1, j^1)\big) + \delta\big[Ew_3(\nu^2, j^2) + E\psi\big(b_3(\nu^2, j^2)\big)\big] \tag{20}$$

Through market incentives, the analyst is induced to minimize bias. Hence the equilibrium condition for b_2 is as follows.

$$b_2^* = \frac{\delta\frac{\partial P_2}{\partial b_2}\Delta\mathrm{w}_3^* + \psi'(b_2^*)}{2\delta[\alpha_{U3}+P(\alpha_{A3}-\alpha_{U3})]} \quad \text{, where} \tag{21}$$

$$\Delta\mathrm{w}_\mathrm{t}^* = w_t^*(\nu^{t-1}, j^{t-1}, j_t = A) - w_t^*(\nu^{t-1}, j^{t-1}, j_t = U) \tag{22}$$

$$\alpha_{\mathrm{kt}}(j^{t-1}) = \frac{h_\varepsilon(j^{t-1}, j_t = k)}{h_t(j^{t-1}, j_t = k)} \tag{23}$$

[13] Note that the precision on the distribution of θ differs based on current employer type and past employers. Moreover, when observing u_t, compared to Employer *U*, Employer *A* is effectively subject to a smaller error term when estimating the mean of θ.

This maximization problem results in the following equilibrium condition for b_1.

$$b_1^* = \frac{\psi'(b_1^*) + \delta \frac{\partial P_1}{\partial b_1} \Delta \mathrm{w}_2^* + \delta^2 \frac{\partial P_1}{\partial b_1} \begin{bmatrix} P \Delta \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{A}) \\ + \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{A}, \mathrm{j}_3 = \mathrm{U}) - \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{U}, \mathrm{j}_3 = \mathrm{U}) \end{bmatrix} + \delta^2 P \frac{\partial P_2}{\partial b_1} \Delta \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{A})}{2\left[\delta \begin{pmatrix} \alpha_{U2} \\ + P(\alpha_{A2} - \alpha_{U2}) \end{pmatrix} + \delta^2 \begin{pmatrix} P^2\big(\alpha_{A3}(\mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_2 = \mathrm{A}) - \alpha_{A3}(\mathrm{j}_2 = \mathrm{U}) + \alpha_{U3}(\mathrm{j}_2 = \mathrm{U})\big) \\ + P\big(\alpha_{U3}(\mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_2 = \mathrm{U})\big) + P\big(\alpha_{A3}(\mathrm{j}_2 = \mathrm{U}) - \alpha_{U3}(\mathrm{j}_2 = \mathrm{U})\big) + \alpha_{U3}(\mathrm{j}_2 = \mathrm{U}) \end{pmatrix}\right]}$$

Proposition A.2 (Hierarchies and Dynamic Incentives) *For sufficiently exclusive hierarchies, privileged analysts are less biased than restricted analysts in early periods and more biased than restricted analysts in late periods.*

Proof of Proposition A.2

By sufficiently exclusive, I am referring to a value of P that is low enough whereby privileged analysts become more biased than restricted analysts in period two.

$$\exists\ \hat{P};\ \forall P < \hat{P},\ b_2^*(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) > \ b_2^*(\mathrm{j}_1 = \mathrm{U}, \mathrm{j}_2 = \mathrm{U})$$

Verify that $\hat{P} = \frac{\alpha_{U3}(\mathrm{j}_1 = \mathrm{U}, \mathrm{j}_2 = \mathrm{U}) * \left(\delta \frac{\partial P_2}{\partial b_2} \Delta \mathrm{w}_3^* + \psi'(b_2^*)\right) - \psi'(b_2^*) * \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A})}{\big(\alpha_{A3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A})\big) * \psi'(b_2^*)}$. Note that wages can be made sufficiently small to ensure that $0 < \hat{P} \leq 1$.

In order to show that Proposition A.2 holds, I need only show that $b_1^*(\mathrm{j}_1 = \mathrm{A}) < b_1^*(\mathrm{j}_1 = \mathrm{U})\ \forall P;\ 0 < P \leq 1$. Let us first compare the numerator for both bias values. In doing so, I invoke the condition that if an analyst does not change his employer, then there is no updating in the wage difference from period two to period three. Hence, $\mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{A}, \mathrm{j}_3) - \mathrm{w}_3^*(\mathrm{j}_2 =$ U,j3 =Δw2 ∗. For privileged analysts, the numerator for $b1*$j1=A is as follows.

$$\psi'(b_1^*) + \frac{\partial P_1}{\partial b_1} \Delta \mathrm{w}_2^*(\delta^2 + \delta) + \delta^2 \Delta \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{A}) \left(P \left(\frac{\partial P_2}{\partial b_1} + \frac{\partial P_1}{\partial b_1} \right) \right)$$

For restricted analysts, the numerator for $b_1^*(\mathrm{j}_1 = \mathrm{U})$ is as follows.

$$\psi'(b_1^*) + \delta^2 \Delta \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{U}) \left(P \left(\frac{\partial P_2}{\partial b_1} + \frac{\partial P_1}{\partial b_1} \right) \right)$$

Note that $\Delta \mathrm{w}_2^* \gg \Delta \mathrm{w}_3^*$ for the employer paths of interest. Given that $\frac{\partial P_t}{\partial b_t} < 0$ and $\Delta \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{A}) > \Delta \mathrm{w}_3^*(\mathrm{j}_2 = \mathrm{U})$, it follows that the numerator for $b_1^*(\mathrm{j}_1 = \mathrm{A})$ is less than the numerator for $b_1^*(\mathrm{j}_1 = \mathrm{U})$.

Let us now compare the denominator for both bias values. For privileged analysts, the denominator for $b_1^*(\mathrm{j}_1 = \mathrm{A})$ is as follows.

$$2 \left[\delta \begin{pmatrix} \alpha_{U2}(\mathrm{j}_1 = \mathrm{A}) \\ +P\left(\alpha_{A2}(\mathrm{j}_1 = \mathrm{A}) - \alpha_{U2}(\mathrm{j}_1 = \mathrm{A})\right) \end{pmatrix} \right.$$

$$\left. + \ \delta^2 \begin{pmatrix} P^2\left(\alpha_{A3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{A3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U}) + \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U})\right) \\ +P\left(\alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U})\right) + P\left(\alpha_{A3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U})\right) \\ +\alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U}) \end{pmatrix} \right]$$

For restricted analysts, the denominator for $b_1^*(\mathrm{j}_1 = \mathrm{U})$ is as follows.

$$2 \left[\delta\left(\alpha_{U2}(\mathrm{j}_1 = \mathrm{U})\right) + \ \delta^2 \left(P^2\left(\alpha_{A3}(\mathrm{j}_1 = \mathrm{U}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{U}, \mathrm{j}_2 = \mathrm{A})\right)\right) \right]$$

Given that $\alpha_{U2}(\mathrm{j}_1 = \mathrm{A}) = \alpha_{U2}(\mathrm{j}_1 = \mathrm{U})$, we can make a comparison with the remaining terms. Such a comparison reduces to the following condition, when satisfied, completes the proof that $b_1^*(\mathrm{j}_1 = \mathrm{A}) < b_1^*(\mathrm{j}_1 = \mathrm{U}) \ \forall P; \ 0 < P \leq 1$.

$$P \begin{pmatrix} \alpha_{A3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) \\ -\alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) \end{pmatrix} (1 - \mathrm{H}) > - \begin{pmatrix} \left(\alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U})\right) \\ + \left(\dfrac{\alpha_{A2}(\mathrm{j}_1 = \mathrm{A}) - \alpha_{U2}(\mathrm{j}_1 = \mathrm{A})}{\delta} \right) \end{pmatrix},$$

$$\text{where H} = \frac{\alpha_{A3}(\mathrm{j}_1 = \mathrm{U}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{U}, \mathrm{j}_2 = \mathrm{A})}{\alpha_{A3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A})}$$

Since $\alpha_{A3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) > 0$, and $0 < P \leq 1, 0 < \mathrm{H} \leq 1$, the left hand side (LHS) of the equation is positive. $\alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) - \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U}) < 0$, so we need only show that $\alpha_{A2}(\mathrm{j}_1 = \mathrm{A}) - \alpha_{U2}(\mathrm{j}_1 = \mathrm{A}) > -\alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) + \alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{U})$. This must be true since $h_1 > h_{U\varepsilon}$, and $h_{U\varepsilon} > 0$. Hence, the numerator for $b_1^*(\mathrm{j}_1 = \mathrm{A})$ is less than the numerator for $b_1^*(\mathrm{j}_1 = \mathrm{U})$, and the denominator for $b_1^*(\mathrm{j}_1 = \mathrm{A})$ is more than the denominator for $b_1^*(\mathrm{j}_1 = \mathrm{U})$ ■

The equilibrium values for bias rise as equilibrium wage differences decrease. Therefore the incentive to be accurate increases with the difference in the wages, which itself is driven by the information advantage. Equilibrium values for bias fall as we increase the effect that accuracy has on being chosen to work for Employer *A*. This is intuitive in that an increase in accuracy makes it more likely that the analyst benefits from a higher wage. Note that the total effect $\delta \frac{\partial P}{\partial b} \Delta \mathrm{w}^*$, is proportional to wage differences. Let us now investigate the main result.

There are two components of Proposition A.2: the early period difference in bias between privileged analysts and restricted analysts (negative), and the late period difference in bias between privileged analysts and restricted analysts (positive). From the perspective of a restricted analyst, the wage difference is zero in period two. In addition, the difference in the incentives to be accurate through Bayesian updating, $\alpha_{A3} - \alpha_{U3}$, is also zero. The reason for both results is that the restricted analyst does not reap the benefits of promotion until two periods ahead of the current period. A privileged analyst on the other hand has an incentive to be accurate through the wage difference and the difference in incentives through updating. But, there exists a cashing-in incentive in that if he is fired by Employer *A*, there is less of an incentive to be accurate when compared to the other analyst since $\alpha_{U3}(\mathrm{j}_1 = \mathrm{A}, \mathrm{j}_2 = \mathrm{A}) < \alpha_{U3}(\mathrm{j}_1 = \mathrm{U}, \mathrm{j}_2 = \mathrm{U})$. Let us say that the wage difference is sufficiently small in period two[14]. The distortion in labor market incentives, at least compared to Holmstrom (1999), occurs when the hierarchy is sufficiently exclusive (P is sufficiently small)[15]. For a privileged analyst and a sufficiently exclusive hierarchy, the effect to be biased dominates the effect to be accurate relative to the restricted analyst.

For period one, wage differences are more important to analysts than in period two. This is related to the effect of the present value of future benefits. Compared to privileged analysts, wage differences from the perspective of restricted analysts are small in period one. In addition, compared to privileged analysts, restricted analysts have less of an incentive to be accurate through Bayesian updating. A key result is that, irrespective of *P*, privileged analysts are motivated to be more conservative than restricted analysts in period one. Moreover, compared to period two, the privileged analyst has no reputation to exploit in moving to Employer *U* since $\alpha_{U2}(\mathrm{j}_1 = \mathrm{A}) = \alpha_{U2}(\mathrm{j}_1 = \mathrm{U})$.

[14] Over time the uncertainty regarding analyst ability is reduced. Therefore wage differences should tend toward zero in an infinite horizon model.

[15] I use the qualifier sufficiently exclusive to refer to the case where the probability of working for Employer A in any period is less than some critical equilibrium value of *P*.