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Investment bank monitoring and bonding of security analysts' research

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Abstract

We assess investment banks' influence over the agreement between their analysts' research behavior and their clients' interests, in the post-reform era. Competing banks discipline their analysts with worse career outcomes for producing biased reports, issuing shirking reports, and for involvement in the earnings guidance game, showing meaningful monitoring of their analysts. Highly reputable banks provide more monitoring discipline of their analysts and bonding of their moral hazard than other banks. The findings agree with the banks taking responsibility for aligning analysts' behavior with clients' interests.

JEL classification: D82, G2, G24, G29, M41.

Keywords: Analysts, Analysts' forecasts, Analysts' recommendations, Career outcome, Earnings guidance, Financial analysts, Financial markets, Herding, Investment banking, Management forecasts, Management guidance, Market efficiency, Piggybacking, Regulatory change, Security analysts, Shirking

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1. Introduction

We assess the influence of investment bank monitoring and bonding of their research analysts after the early 2000s reforms. In this period the banks are the leading employers of analysts among financial service firms and they nearly tripled their supply of earnings forecasts. We study the alignment of analysts' research behavior with the interests of the banks' research clients, using the sensitivity of analysts' career moves to their use of biased and shirking reports. A biased report is skewed from expectation, influencing clients' decisions to better serve the analyst's interests. A shirking report serves the analyst's self-interest by free-riding on public sources and using little of the time, effort and real resources required for a meaningful report. Therefore neither report is likely to provide clients with useful advice or information, and both could serve clients sub-optimally. Career outcomes are measured by analysts moving either up to a more reputable bank, down to a less reputable bank, or leaving the profession (Mikhail et al. 1999, Hong et al. 2000, Hong and Kubik 2003). Effective monitoring and bonding should align analysts' reporting with clients' interests, resulting in better career outcomes, on average.[1]

The bank monitoring hypothesis predicts that the banks, and thus their managers, incented by competition, will monitor and discipline their analysts to act in clients' interests, punishing biased reporting and report shirking. To measure bias we consider two traits: report optimism (Hong and Kubik, 2003) and report boldness (Hong et al. 2000), both of which are extreme reports relative to the consensus. Two other traits measure shirking: report piggybacking, when the analyst's report herds on other analysts' reports (Truman, 1994; Graham, 1999; Cooper et al. 2001), and news piggybacking, when the analyst's report mimics recent news and extreme returns (Altınkılıç and Hansen, 2009; Altınkılıç et al., 2013).[2]

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[1] Previously analysts often wrote reports in their own self-interests, in conflict with those of their clients. A striking case is optimistically biasing their earnings forecasts to lure underwriting and trading business that boosts bank revenues and thus analysts' bonus income. Issuing optimistic reports for capital raising firms in the bank's underwriting arm is widely reported. For analysts' literature reviews see Kothari (2001) and Kothari et al. (2016). See also Mehran and Stulz (2007).

[2] Herding is studied by Scharfstein and Stein (1990), Banerjee (1992) and Bikhchandani et al. (1992). For copying certain analysts, see Welch (2000), Cooper et al. (2001), Altınkılıç and Hansen (2009), and Guttman (2010). Herding has many meanings; for example, to track other analysts' recent reports, a report timing notion, or a recent consensus among analysts, a

The bank reputation hypothesis predicts more reputable banks will discipline their analysts more strictly for biasing reports and report shirking. The bank puts its reputation on the line to assure clients of reliable monitoring, and to reduce concern with analysts' moral hazard when they could issue self-interested reports while shirking their risk. More reputable banks thus expect higher costs of producing research and greater future quasi-rents for their reputations. To be effective the bank's reputation bond value must exceed the expected value of benefits the bank would receive by letting analysts issue faulty reports.[3]

The first contribution of this article is new findings that show excess report bias and report shirking are harmful for analysts' careers. This is consistent with the monitoring hypothesis. The second contribution is new evidence showing the more reputable banks discipline their analysts more severely than other banks. This agrees with stricter monitoring by more reputable banks while assuring their report reliability.

We examine a third, earnings expectations hypothesis, that the reports are often a result of analysts engaging in the earnings expectations game with firm management. For example, an analyst may initially issue an overly optimistic forecast, management then issues forecast to walk the analyst through revising her forecast down to a level management can comfortably meet or beat, creating a false image of good firm performance and also reports that are more likely to mislead clients.[4] In exchange, firm management directs future business to the analyst's bank, boosting the bank's revenues that are partly used to reward the cooperating analysts. Thus, the earnings expectations hypothesis predicts analysts who slavishly

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report level notion which also is the reverse of boldness. Herding also refers to other uses that do not relate directly to analysts (e.g., see Graham, 1999, Welch, 2000). Recent analyses of news piggybacking include Altınkılıç and Hansen (2009), Loh and Stulz (2011), Altınkılıç et al. (2013), Kim and Song (2014), Li and You (2015), and Altınkılıç, et al. (2016). Discarding information is noted in Trueman (1994) and Graham (1999). Harford et al. (2016) also note analyst shirking.

[3] Although the need to bond analysts' moral hazard behavior is often overlooked, authors recognize the necessity for resolving other finance agents' moral hazard behavior (Axelson and Bond, 2015, Glode et al., 2016, Glode and Lowery 2016). For discussion of moral hazard see Holmström (1979). Cowen et al. (2006) provide an early insightful recognition of analysts' lemons problem.

[4] We thank Adam Kolasinski for suggesting the expectations management hypothesis. For discussion of the walk down phenomenon, see Richardson et al. (2004), Cotter et al. (2006), and Bradshaw et al. (2016). The emphasis on short-term earnings is noted in Bhojraj et al. (2009), Feng and McVay (2010) and He and Tian (2013), and Bradshaw et al. (2016), among others. That analysts may respond to managements' guidance by issuing a final meetable or beatable earnings target is taken up in Richardson et al. (2004), Cotter et al. (2006), Bhojraj et al. (2009), Doyle et al. (2013), Heflin et al. (2016), and Kim and So (2017). Potential benefits from using guidance include those available from currying favor with management (Feng and McVay, 2010), improved equity-based compensation (Lys, et al., 2008), and gains in investment banking business (Feng and McVay, 2010).

follow earnings guidance will be rewarded by bank management for issuing the reports that tend to not serve clients' interests. However, given bank competition and monitoring, the monitoring hypothesis predicts bank management will punish such slavish analysts for issuing reports that are not in the clients' interests. Further results from a number of tests reject the expectations management hypothesis and they agree with the monitoring hypothesis. These findings expand the evidence of bank monitoring of their analysts' sub-optimal reporting.

The findings are confirmed using other designs of the careers dependent variable, alternate measures of bank reputation, and a later start for the post-reform era in 2003 after the passage of every major reform. The earnings forecast report findings are confirmed using analysts' other major report, recommendations to buy, sell, and hold followed firms' common stock.

The new findings extend the literature in a number of ways. They reveal a facet of investment bank reputation that has received little attention from researchers in the past. While bank reputation previously did not have a significant influence on analysts' research (Fang and Yasuda, 2009), we find that bank reputation has a significant impact post-reform, especially for more reputable banks.[5] Second, although analysts' over-optimistic reports were rewarded with favorable career outcomes before the reforms (Hong and Kubik 2003), new results show the banks punish analysts' careers for optimism after the reforms, including long-term forecast optimism. This is the case at all banks and significantly more so at the higher reputation banks.[6] The finding that boldness bias is bad for careers confirms findings by Hong, et al. (2000), but it is contrary to other findings that suggest boldness signals valuable new information (Gleason and Lee, 2003; Clement and Tse, 2005). A fourth finding shows report piggybacking impacts

[5] Bank reputation traditionally addresses investor concerns with a lemons problem, certifying the pricing of security offerings underwritten by the bank, like IPOs and SEOs, and providing credible advice to management. A broad literature shows it is common for the banks to use their reputations to bond their intermediation of financial services. Cases of bonding when promises to monitor long-term performance are joined by a reputation bond include: equity offerings (Smith, 1977, 1986, Hansen and Pinkerton, 1982, Gilson and Kraakman, 1984, Beatty and Ritter, 1986, Booth and Smith, 1986, Beatty, 1989, Carter and Manaster, 1990, Eckbo and Masulis, 1995, Altınkılıç and Hansen, 2000, Ritter and Welch, 2002, and Ljungqvist, 2007); private equity deals (Demiroglu and James, 2010, Ivashina and Kovner, 2011, Harford and Kolasinski, 2013, and Huang et al. 2016); venture capital deals (Megginson and Weiss, 1991, Gompers and Lerner, 1999, Nahata, 2008, and Krishnan et al. 2011); syndicated loans (Chemmanur and Fulghieri, 1994, Sufi, 2007, and Gopalan et al. 2011), and information externalities, see Leland and Pyle (1977), Klein and Leffler (1981), Kreps and Wilson (1982) and Diamond (1991). For discussion of intermediated offerings of risky securities, see Baron and Holmström (1980) and Baron (1982).

[6] We replicated in the pre-reform period the Hong and Kubik (2003) finding that optimism is rewarded with career improvement, supporting the post-reform change (see footnote 12).

careers negatively, and a fifth finding shows that news piggybacking also affects careers negatively. These new findings are consistent with the view that piggybacking behavior is typically free-riding and shirking (Altınkılıç and Hansen, 2009; Loh and Stulz, 2011; Altınkılıç et al. 2013; Kim and Song, 2014; Hansen, 2015; Li and You, 2015), contrary to the established idea that herding on others' reports is good for analysts as a way to build personal reputations, despite the shirking (Trueman, 1994; Graham, 1999). If herding builds reputation then it should be good for the analyst's career. Also, the negative career impact of news piggybacking behavior acts more like punished free-riding conduct than analysts' rapidly extracting new information that is embedded within recent news (Yezegel, 2015). If analysts' extraction consistently provides enough new information to dominate news piggybacking by other free-riding analysts, then news piggybacking should also be good for analysts' careers. However, the findings do not support the reputation building story, nor the information extraction story, on average. Lastly, new findings from three more tests indicate that bank oversight punishes engaging in the earnings guidance game. The new findings agree with the emergence of the analyst facet of bank reputation after the Global Settlement and other relevant reforms that impact analysts' behavior and the research role of the banks.[7] These changes demonstrate that, as employees of competitive investment banks, successful analysts are not free to behave as independent agents and are more responsive to clients' interests.[8]

One concern is with identifying the interests of the two agents, analysts' interests and clients' interests. Stable recognition of their objectives is assured by what we call the principle of revealed choice:

[7] The reform era was ushered in by six major reforms: Regulation Fair Disclosure (Reg. FD, 2000) mandates publicly traded firms must disclose their material information concurrently to all investors; the Sarbanes-Oxley Act (SOX, 2002) requires firm managers to certify the accuracy of financial information, implemented penalties for fraudulent financial activity, and raised the oversight role of directors and the independence of the outside auditors of corporate financial statements; NASD Rule 2711 and NYSE Rule 472 (both in 2002) target biased analysts' research by severing ties between their investment bank arms; The Global Research Analyst Settlement (Global Settlement, April, 2003), between the SEC, the NYSE, the NASD, and the New York Attorney's General Office, fined ten of the largest investment banks $1.4 billion, and forbid their analysts from participating in IPO road shows; and Regulation Analyst Certification (2003) requires analysts disclose possible conflicts regarding their compensation.

[8] Surveys also reveal that analysts are more attentive to clients' interests after the reforms (Brown et al., 2016). Yet, as noted by Bradshaw (2009, 2011) and Leuz and Wysocki (2016) it is not possible to pinpoint the particular impact of each reform. Other changes in the post-reform supply of research noted by researchers include a drop in recommendations, reductions in their informativeness, a decline in optimism, better alignment of recommendations with earnings projections, severing analysts' compensation from their banks' underwriting business, and behavioral changes in hiring and training analysts. See Barber et al. (2006), Ljungqvist et al. (2006, 2009), Barniv et al. (2009), Chen and Chen (2009), Kadan et al. (2009), Guan et al. (2012), Altınkılıç et al. (2013), Altınkılıç et al. (2016), and Corwin et al. (2017).

competition pressures bank managers to monitor their analysts and discipline those who produce too many self-interest reports and rewards those whose reports align best with client-interests, creating agreement between report type and career outcome, on average. Managers can evaluate the bias and shirking by comparing analysts' reports with the followed firms' performance. Clients and rival banks can make similar assessments. If the monitoring is not effective current and prospective clients will take their future business to rival banks for better reports. At the more reputable banks, which sell tens of thousands of reports yearly, losing even a modest portion of clients can have a sizeable effect. The banks' monitoring impact on analysts' behavior will therefore be visible in cross-section regressions of their career outcomes on their report types.[9]

We recognize that analysts could put their personal reputations on the line to calm client concerns with their moral hazard, perhaps displacing the economic role of bank reputation. Studies do show that analysts realize personal reputation gains from winning the prestigious *Institutional Investor Award* (*II Award*) (Emery and Li, 2009; Fang and Yasuda, 2014; Maber et al. 2014). However, we show that the value expected from winning the *II Award* is not enough to bond the typical analyst's reports, as the odds of winning the *II Award* are simply too small (below 1%). The limited ability of personal reputation to protect clients raises further the unique role of bank reputation in resolving analysts' moral hazard.

The remainder of the article proceeds as follows: Section 2 discusses the sample and the central report characteristics used in this article; Section 3 reports evidence of competition in the supply of analysts' research; Section 4 reports results from testing the bank monitoring hypothesis; Section 5 examines the reputation hypothesis; Section 6 examines the expectations management hypothesis; Section 7 reports robustness tests and examines the influence of personal reputation; Section 8 concludes the article.

2. Data and methodology

[9] The principle of revealed choice, that the research objectives of analysts employed at value maximizing banks are identified by their career movements, on average, is like Samuelson's (1938) revealed preference by utility maximizing consumers. Managers judge report bias and shirking using their experience with thousands of reports, insights from other managers, and learning from other information about analysts' reports and firms' actual performance. The principle suggests career moves correctly identify the biased and shirking bank analysts, on average. Evidence of competition pressure on analysts is in Gande et al. (1999), Hansen (2001), Hong and Kacperczyk (2010), Ellis et al. (2011), and herein.

2.1 The sample

The Full Sample of analysts and their reports described in Appendix A includes almost 16 million earnings forecasts by 17,213 analysts, and nearly 600 thousand stock recommendations by 15,379 analysts over 2001-2014, from the I/B/E/S file (Table 1, Panels A and B).[10] The Shorter Sample (2003-2014) period permits a reevaluation of important previous findings for changes that occur in a distinctly new economic setting.

The impact of analysts' research on their careers is assessed using their forecasts of the followed firms' earnings, as well as their recommendations to buy or sell the firms' stock, which range from 1 (strong buy) to 5 (strong sell). Each report is classified as a downgrade (upgrade) if its current value is below (above) the pre-existing value from the same analyst for the same company and fiscal period. Overall, 53% of the forecasts are downgrades and 44% are upgrades, 43% of the recommendation changes are downgrades and 35% are upgrades, and the remaining reports are initiations and reiterations (Table 1). The report time stamps reveal whether the reports are issued in trading hours (9:30 to 16:00 on trading days), or in non-trading hours including weekends and holidays. Both forecasts and recommendations are more common in non-trading hours, with frequencies of 60% and 54% respectively (Table 1).

2.2 The main variables

Here the main variables used in the analysis are discussed. For further description of how these and all other variables are constructed see Appendix B.

2.2.1 Career performance

[10] Merrill Lynch is in the sample for 2010-2013, but otherwise like Lehman Brothers is not available, as I/B/E/S excludes both banks' historical reports after 2007. Four investment banks did not make the sample top list due to too few I/B/E/S analysts (in parentheses is the annual mean number of reports, and I/B/E/S years): Nomura Securities Int. (1, 5); Wells Fargo Securities (23, 6); BNP Paribas (5, 14); and Societe General (12, 11.4). Also unavailable are I/B/E/S banks that are not found on the BRAN file: Lazard Freres (only Lazard Cap Markets is found), Fleet Boston, Montgomery Securities, Barclays, Mizuho, Sumitoma Mitsui. A large firm with I/B/E/S code 543 could not be identified. A gauge of the stature of the omitted banks is their Carter and Manaster (1990) reputation measure, obtained from Ritter's web page, which are parsed into uneven periods: 92-00, 01-04, 05-07, 08-09, 10-11, and 12-14. 9.001 is the highest stature banks. Those of rank 7.001; BNP Paribas (92-00), Societe Generale (92-00), FleetBoston (92-00 and 01-04). Those at 8.001; Wells Fargo (10-11), BNP Paribas (10-11: 12-14), Societe Generale (10-11: 12-14), Lazard Freres (08-09: 10-11), Fleet Boston Robertson Stephens (92-00), Montgomery (92-00), and Barclays (08-09: 10-11: 12-14). Those at 9.001; Nomura (92-00) and Lazard Freres (92-00: 01-04).

Because information on analysts' compensation, internal promotions and demotions, and other interesting pieces of the banks' information concerning their analysts' history are not available from public sources, their career outcomes cannot be identified using these characteristics and data. Following Mikhail et al. (1999), Hong et al. (2000), and Hong and Kubik (2003), the source of the career outcome measure is analysts' switching from one investment bank to another bank, or departing the profession. The banks are sorted by the number of analysts they employ each year and then ranked from the biggest employer to the lowest into deciles. Deciles are formed in such a way that each decile contains roughly the same number of employed analysts. Larger banks employ many more analysts compared to smaller banks. Thus, the top decile includes only two of the largest investment banks, whereas the bottom decile has many small brokerage firms.

The career outcome, denoted $Career_{i,t}$, is measured by analysts' switching from their current bank to a job at another bank. This variable captures analysts' movements up and down the bank prominence deciles that are formed by ranking the banks by the number of analysts they employ. Therefore, while most analysts do not switch employers in a given year, we can observe those who move up to a higher decile, and thus to a more reputable bank, and those moving down to a lower decile, and thus a less reputable bank. We can also observe those moving laterally in the same decile or who depart the profession, which happens in the last year they are in the database.

The central career outcome measure is a three-level ordinal variable: the analyst switches up (high), makes no switch or changes laterally within the same decile (middle), or switches down or departs the profession (low). This measure extends Mikhail et al. (1999) who do not distinguish good and bad outcomes, Hong et al. (2000) who do not consider demotions, and Hong and Kubik (2003) who do not include departing analysts. To avoid biasing the estimation due to the inability of analysts in the top decile to move up and those in the bottom decile to move down, the top and bottom deciles are removed from the Probit analyses. Thus, analysts in every decile can move up or down. Because the larger banks employ many more analysts, excluding the top decile removes on average only two of the top banks, so the vast majority of banks remain in the analyses. Switching to a higher (lower) decile is a favorable (unfavorable) career outcome.

Two alternative career outcome measures are also examined. One uses a four-level Probit; move up to a higher decile employer (highest), no change or change within the same decile (middle), move down (low), and leave the profession (lowest). The third approach uses three separate binary Probits, one estimated for moving up to an employer in a higher decile, one for moving down, and one for departing the profession.

[Insert Table 1 about here]

2.2.2 Analysts' report bias

One purpose of this article is to understand the career consequences for analysts who tend to bias their reports or tend to shirk in their reporting. Because bias and shirking cannot be directly identified, proxy traits for both are used. For robustness, two traits for bias are tested and two traits for shirking are tested.

The two bias traits, report optimism and report boldness, reflect extreme reports, on average. *Optimism*, measured at the analyst level, is the fraction of all forecasts issued by the analyst during the year that exceed the consensus forecast of all other analysts, which draws from Hong and Kubik (2003). *Optimism* measures bias because the analyst has set the forecast above the current mean forecast, which is expected by theories of biased forecasts. Hong and Kubik (2003) document that in the pre-reform era the more optimistic analysts were more likely to experience favorable job switches. The second bias trait, *Boldness*, is computed following Hong et al. (2000). First, the deviation of each forecast from the benchmark consensus is computed. Next, all analysts who follow a given firm in a given year are ranked based on these deviations. They are then assigned a boldness score based on that ranking. Forecast *Boldness* is the average of the analyst's boldness scores in year *t*. *Boldness* can account for very favorable or very unfavorable forecasts. *Boldness* also measures bias because it reflects how much the analyst's report deviates from the consensus. Because both *Optimism* and *Boldness* require the consensus estimate, they can be calculated only for analysts' earnings forecasts and not for their recommendations.

The alternate bias measures behave somewhat similarly, reflecting in part similar underpinnings (Fig. 1). In agreement with *Optimism* and *Boldness* being alternate proxies for bias, their co-movement is most apparent when *Optimism* is larger.

[Insert Figure 1 about here]

2.2.3 Analysts' report shirking

For the first time in analyst career analyses we consider the career impact of two shirking traits. The first trait, *ReportPiggybacking*, for analyst *i* during year *t*, is the fraction of all the analyst's forecasts that follow within three days a forecast by another analyst issued for the same followed firm. Piggybacking forecasts are thus similar to other analysts' recent forecasts for the same firm. These reports are therefore a herding form of shirking, which should negatively impact the careers of analysts who tend to herd more (Welch, 2000, Cooper et al. 2001, Guttman, 2010).

The second shirking trait, *NewsPiggybacking*, is measured following Altınkılıç et al. (2013). *NewsPiggybacking*, computed for the first time at the analyst level, is the fraction of all forecasts issued by the analyst during three days after an earnings announcement or company issued guidance, "key events" (following Altinkilic et al. 2013), or a large return. As information processors, analysts update reports for their investors after key events. *NewsPiggybacking* will therefore be appreciated because it keeps reports aligned with public information, especially following a high concentration of news. In effect, investors therefore delegate to security analysts the task of staying abreast of relevant public information about the firm.[11] However, by simply free-riding on the public information contained in the recent news and key events, the piggybacking report is unlikely to convey new private information, and most often reflects analysts' shirking and avoiding any significant research effort. Thus, the free-riding

[11] See Lys and Sohn (1990), Stickle (1992), Trueman (1994), Healy and Palepu (2001), Lim (2001), Gleason and Lee (2003), Jackson (2005), Groysberg et al. (2011), and Yezegel (2015).

reports rarely provide new information and are less effective, making *NewsPiggybacking* a shirking trait that should be associated with worse career outcomes, on average (Altinkilic and Hansen, 2009, Loh and Stulz, 2011, Altinkilic et al. 2013, and Kim and Song, 2014).

While much academic research has focused on the bias traits, *Optimism* and *Boldness*, there is little evidence of shirking behavior. Yet, the two shirking traits, *NewsPiggybacking* and *ReportPiggybacking*, can also be computed for analysts' second important report, stock recommendation changes. This is because their calculation does not use a consensus measure. Figure 1 B shows similar co-movement of the two shirking traits. Both *NewsPiggybacking* and *ReportPiggybacking* can occur at the same time. For example, a firm announcement of an acquisition that has significant value-added implications may surprise investors. Some analysts could quickly piggyback on the news alone while others may piggyback on the associated extreme return reactions, or both. Others may follow the first mover's reaction to the news.

2.2.4 Analysts' report Accuracy and job Experience

Throughout the tests of bias and shirking impacts on career outcomes, two control variables are used; one for analysts' report accuracy and one for their experience. Mikhail et al. (1999), Hong et al. (2000), and Hong and Kubik (2003) find reporting accuracy significantly reduces analysts' job changes. This article follows Mikhail et al. (1999) to measure *Accuracy*. To compute relative *Accuracy*, all analysts following the firm during year t are ranked based on their $Error_{i,j,t}$, $Error_{i,j,t} = (F_{i,j,t} - E_{j,t}) \div p_{-5}$, where $F_{i,j,t}$ is analyst's i's forecast for company j earnings during year t, $E_{j,t}$ is the firm's actual earnings during year t, and p_{-5} is the CRSP stock price 5 days before the forecast. *Accuracy* is relative to that of all other analysts with the same primary industry following the same firm during year t. These n comparison analysts, which could be employed at the same employer, must have the same primary industry and have issued at least one forecast for each quarter of the year for the firm for which they serve as a comparison group. Only firms that are followed by five or more analysts are included. All n analysts are ranked based on their accuracy in a given year, where the most accurate analyst rank is n, then we divide this rank by n, so rank ranges from 1/*n* to 1, with high levels corresponding to relatively more accurate analysts, and represents analyst *i*'s accuracy rank for firm *j* and year *t* relative to his cohort analysts. The rank accuracy statistic for analyst *i* and year *t* is her average rank for the year.

Following Mikhail et al. (1999), *Experience* is the number of years the analyst has been in the database as of year *t*.

2.2.5 Reputation measures

Our analysis explicitly recognizes the economic role of the analyst's employer's reputation in capital markets as a force that disciplines analyst behavior. Three measures of bank reputation are examined: *Top10Bank*s, a binary indicator for the top 10 banks in the market for analysts, a corresponding binary indicator for *Top25Bank*s, and one for top reputation banks identified using the updated Carter and Manaster (2000) IPO lead underwriter ranking, *CMLRBanks*.

3. The competitive supply of research

Prior research has shown there is significant competition between investment banks in several product markets in the U.S. and worldwide (Gande et al. 1999; Hansen 2001; Hong and Kacperczyk 2010; Ellis et al. 2011). Entry barriers into investment banking have been low, as many banks entered into the industry top echelon over the sample period and many top banks have exited the industry (e.g., Bear Sterns, Dean Witter Reynolds, Donaldson Lufkin Jenrette, Lehman Brothers, Merrill Lynch, Paine Webber, Prudential Bache, Prudential Equity, Robertson Stephens, and Salomon Brothers). Such competition pressures the investment banks to maximize value, which includes developing their research to serve client demand for credible reports at low cost. To be unresponsive to demand leads clients to switch to rival banks for responsible research at competitive costs.

While there is much evidence of competition in the banks' product markets, there is little published evidence that we are aware of that reveals bank competition in the analyst market. Of the 30 biggest employers of analysts, which includes the Top 10 and Top 25, all but three are investment banks (Table 2, Panel A). Two indicators of intense competition are low concentration and ease of entry. In the market for analysts in the Full Sample, 4,245 (28%) of the analysts work at a top 10 bank, 3,584 (24%) work at the next 11-30 banks, and the remaining 7,096 (48%) work at smaller banks and financial service firms (Table 2 Panels A and B). Annual employment is stable around the industry mean of 4,165 during much of the sample period, with a mild increase over the last three years (Table 2 Panel C). Concentration of the banks' market shares of the analyst market is low; a *Top10Bank*'s average market share is 5.5%, and no bank share exceeds 7% among the largest ten banks, except the 10.5% for Merrill Lynch before the crisis ended (Table 2, Panel A and Panel B). The analyst employer market Herfindahl-Hirschman Index is quite low for the top 10 (top 30 and top 50) employers, at 0.022 (0.027 and 0.031), showing a high level of competition and no sign of monopoly or oligopoly power. There have been no dominant analyst employers over the sample period.

[Insert Table 2 about here]

Average entry into and exit out of the analysts' labor market each year are 959 and 987 analysts respectively, hence a yearly average turnover of 23% (Table 2, Panel C). Analysts' retention at three years' experience is 64% at a top 10 bank, 65% at top 11-25, and 56% at a bottom bank. After five years it is respectively 42%, 41%, and 34%. After ten years it is respectively 19%, 25%, and 17%.

The competition between the banks, in their several financial product markets (e.g., consulting, trading, corporate transactions, equity markets, bond markets, and more) as well as in the analyst labor market, keeps pressure on the banks and thus their managers to monitor and discipline their analysts' research. Bank managers regularly track and assess their analysts' performance, punishing those who are likely to create research in their own interests, and rewarding those who tend to produce research in bank clients' interests.

4. Bank monitoring hypothesis

This section reports results from testing the monitoring hypothesis; that investment banks monitor and discipline their analysts. Consequently, misleading reports will have negative effects on analysts' career outcomes, on average.

4.1 Analysts' Bias and shirking

The sensitivity of analysts' careers to their report bias and shirking is tested first with the following ordered Probit model,

$$Career_{i,t+1} = \beta_0 + \alpha Accuracy_{i,t} + \gamma Experience_{i,t} + \beta_j Trait_{j,i,t} + error_{i,t} \quad (1)$$

where *i* denotes the analyst, during year *t*, the *j* subscript denotes the analyst's bias and shirking reports, and the model includes control variables for analysts' forecast *Accuracy* and job *Experience*.

Throughout, all test statistic standard errors are adjusted for clustering along two dimensions, analyst and main followed industry, following Thompson (2011)[12]. For each analyst during the year, the main industry, defined using a two-digit SIC code, is identified based on the number of followed firms. All regression models include year and employer fixed effects. We also try clustering along analyst and year dimensions, with broker and main industry fixed effects. The results are qualitatively the same.

The first estimation (Table 3, Column 1) shows forecasts with greater *Accuracy* or more *Experience* have significantly positive impacts on the analyst's career. We then proceed with estimating the effect of *Optimism* (j=1) on *Career*. The estimation shows issuing more optimistic forecasts has a significantly negative impact on the analyst's *Career* (Table 3, Column 2). This agrees with the investment bank monitoring hypothesis. Note this negative impact of *Optimism* differs distinctly from the Hong and Kubik (2003) finding that optimism has a positive impact on analysts' careers. Thus, optimism is punished in the post-reform era, in contrast with the pre-reform era. In unreported results, we also found optimism has a

[12] We thank Adam Kolasinski for suggesting the adjustment of the standard errors for clustering.

positive impact on careers in the pre-reform era, in agreement with Hong and Kubik (2003).[13] The new finding thus agrees with a change in disciplining analysts following the reforms.

[Insert Table 3 about here]

The findings in Column 3 show that analysts who exhibit greater *Boldness* (j=2), the second bias trait, also experience significantly negative career effects. This agrees with the Hong et al. (2000) finding in the pre-reform era. It also agrees with the investment bank monitoring hypothesis. Still, some theories argue that boldness signals analysts' information, which suggests boldness should therefore benefit careers (Gleason and Lee, 2003, Clement and Tse, 2005). However, in the post-reform era the results show boldness is a form of bias that leads to poor career outcomes.

Taken together, these results show that the competitive banks punish biased forecasts by shortening analysts' careers. Additionally, both *Accuracy* and *Experience* have significantly positive impacts on analysts' careers, confirming similar results in earlier studies.

The findings reported in Table 3 Column 4 show that *ReportPiggybacking* (j=3) forecasts have a significantly negative impact on analysts' careers. In Column 5 *NewsPiggybacking* (j=4) negatively affects analysts' careers. These new findings disagree with the theories that presume *ReportPiggybacking* and *NewsPiggybacking* largely embody new information that analysts have rapidly extracted from the news, and thus contribute to a significant stock price reaction that raises firm value, which is expected to be good for analysts' careers.

As *ReportPiggybacking* and *NewsPiggybacking* do not require a consensus measure for their calculation, they can also be computed for the analysts' second important report: stock recommendation changes. Consider, therefore, the sensitivity of careers to shirking using analysts' stock recommendations. An increase in *ReportPiggybacking* or *NewsPiggybacking*, for recommendations, has a significantly negative impact on analysts' careers (Table 3, Panel B, Columns 4 and 5). These findings for the

[13] Our estimates of their regression models for *Moves Up* and for *Moves Down*, are *Moves Up* = 13.3*** + 0.4*** × *Accuracy* – 0.05*** × *Experience* + 0.26*** × *Optimism*; and *Moves Down* = – 2.9*** – 1.1*** × *Accuracy* – 0.02*** × *Experience* – 0.12*** × *Optimism*. Where *** indicates significantly different from 0 at the 1% level in a two-tail test.

recommendation shirking report therefore corroborate the qualitatively similar findings for the shirking report in the case of earnings forecasts. Note in both regression tests for shirking that *Accuracy* and *Experience* have a significantly positive impact on careers. The results showing analysts who use biased or shirking reports have shorter careers agree with the hypothesis that investment banks monitor their analysts and punish those with biased or shirking forecasts, or with shirking recommendations.

5. Bank reputation hypothesis

The findings thus far support the employer monitoring hypothesis, that the banks monitor their analysts, provide oversight discipline and supervision of their reporting, and punish their analysts for subpar reporting. They agree with an active bank controlling role in analysts' decision-making.[14] This section examines tests of the reputation hypothesis.

5.1 The significance of bank reputation: The case of earnings forecasts

To test the employer reputation hypothesis the following extension of the basic ordered Probit model is estimated;

$$\begin{aligned} Career_{i,t+1} = \beta_0 + \alpha Accuracy_{i,t} + \gamma Experience_{i,t} \\ + \beta_{1j}\, Trait_{i,j,t} \times TopBank_{i,t} + \beta_{2j}\, Trait_{i,j,t} \times BottomBank_{i,t} \\ + error_{i,t} \qquad (2) \end{aligned}$$

The compactly written model continues with the conventions; when $j = 1$ ($j = 2$) bias is measured with *Optimism* (*Boldness*) and when $j = 3$ ($j = 4$) shirking is measured using *ReportPiggybacking* (*NewsPiggybacking*), for analyst i during year t.

[14] Regarding the background question of what value analysts' research adds in competitive securities markets, researchers have identified a number of answers. Analysts can raise monitoring of followed firms' management and operations that ultimately increases firm value, noted early by Jensen and Meckling (1976), and shown later by Bhushan (1989), Moyer et al. (1989), Chung and Jo (1996), Hayes (1998), Yu (2008), Altınkılıç and Hansen (2009), Demiroglu and Ryngaert (2010), Jung et al. (2012), Altınkılıç et al. (2013), Derrien and Kecskes (2013), Kim and Song (2014), Chen et al. (2015), Hansen (2015), Li and You (2015), and Altınkılıç et al. (2016). As custodians, analysts also lower information asymmetry between better and less-well informed investors, thus lowering the cost of capital. See Womack (1996), Barber et al. (2001), Gleason and Lee (2003), Barber et al. (2007), Bowen et al. (2008), Cohen et al. (2010), Derrien and Kecskes (2013), Hansen (2015), and Li and You (2015). Recent findings suggest it is unlikely that analysts or investment managers consistently provide investors with valuable, brand new information that is not already public. See Barber et al. (2001), Altınkılıç and Hansen (2009), Altınkılıç et al. (2013), Altınkılıç et al. (2016), Jenkinson et al. (2016), and Kolasinski and Kothari (2008).

The base regression model is therefore expanded after identifying the group of the analysts' employers. One group is identified by the *TopBank* binary variable that equals one when the analyst's employer is a Top 10 investment bank, and the other is indicated by the *BottomBank* binary variable denoting the analysts employed at other banks. Thus, *BottomBank* = 1- *TopBank*. This use of two mutually exclusive reputation binary variables directly presents the estimates for the separate impacts of bias and shirking in each reputation class.[15] Because the largest banks employ the most analysts, excluding the top decile leaves a super majority of 80% and higher of top banks in the analyses (eight of the top 10 and 23 of the *Top25Bank*s), so there is ample variation in the *TopBank* binary variable.

Regression model (2) therefore directly compares how each trait impacts for analysts employed at top banks with the impacts for analysts at the bottom banks. The estimations include both year and employer fixed effects.

5.2 Bias

Consider first the impact of employer reputation on careers for analysts who issue biased forecasts. *Optimism* has a highly significant negative impact on *Career*, for analysts at both the top banks and at the bottom banks, which have high and low reputation capital respectively (Table 4, Panel A, Column 1). These results are consistent with all banks, top and bottom, disciplining their analysts for issuing optimistic forecasts. However, the response to optimism for analysts employed at a *Top10Bank* is greater than the response to optimism for analysts employed at a bottom bank. Furthermore, both are statistically significant. This agrees with the top banks applying more severe career discipline.

Consistent with the reputation hypothesis, *Boldness* has a significantly negative impact on analysts' careers. However, the impact of *Boldness* is significantly greater for the analyst is employed at a *Top10Bank* versus at a bottom bank (Table 4, Panel A, Column 2).

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[15] Our specification, $\beta_{1j}Trait_{i,j,t} \times TopBank_{i,t} + \beta_{2j}Trait_{i,j,t} \times BottomBank_{i,t}$, differs from a common specification that would include *Trait* linearly and with interaction with *TopBank*; $\pi_{m1}Trait_{i,m,t} + \pi_{m2}Trait_{i,m,t} \times TopBank_{i,t}$. The estimated top bank reputation effect is assessed manually by calculating $\hat{\beta}_{j1} = \hat{\pi}_{m1} + \hat{\pi}_{m2}$, our specification provides these computations and the standard errors directly. In unreported tests we find that using the classical specification, $\beta_{1j}Trait_{i,j,t} + \beta_{2j}Trait_{i,j,t} \times TopBank_{i,t} + TopBank_{i,t}$ yields the same results.

The findings show that top banks punish security analysts more severely for biased reporting than do the bottom banks. These results are consistent with the monitoring and the reputation hypotheses.

[Insert Table 4 about here]

5.3 Shirking

Consider next how bank reputation impacts the careers of those analysts who shirk in their reporting. The results show that the analysts who issue report piggybacking earnings forecasts have shorter careers than do other analysts. Moreover, the negative career consequences are significantly more severe for the analysts who are employed at a top bank than for analysts employed at a bottom bank (Table 4, Panel A, Column 3).

The second shirking trait, *NewsPiggybacking,* also has a significantly negative impact on analysts' careers, and much more so at more reputable banks (Table 4, Panel A, Colum 4).

The shirking results are therefore consistent with the higher reputation banks punishing security analysts more severely for shirking than the lower reputation banks.

5.4 The significance of bank monitoring: the case of stock recommendations

To confirm the robustness of the monitoring evidence, we examine analysts' second important report: their recommendations to buy, hold, or sell the stock. The *Top10Bank* reputation finding is corroborated again: *ReportPiggybacking* recommendations have a significantly more negative impact on the careers of analysts who are employed at a *Top10Bank* than the careers of those employed at a bottom bank (Table 4, Panel A, Column 5). Likewise, *NewsPiggybacking* recommendations have significantly more negative impact for the analysts who work at a top reputation bank than for analysts who work at a bottom reputation bank (Table 4, Panel A, Column 6). Note they also have negative impacts on analysts at bottom banks, but less so. In each of the estimations, the impacts on careers of forecast *Accuracy* and *Experience* are significantly positive.

This evidence from analysts' stock recommendation reports therefore confirms the findings when using their earnings forecasts.

5.5 Alternative bank reputation measures

Consider next the robustness of the results to the use of a more generous bank reputation measure, expanding the *TopBank* variable to include every top 25 employer, which are almost always investment banks (see Table 2), where the rank is based on the bank's share of the analysts' labor market.

Using the *Top25Bank* reputation measure the basic findings are qualitatively similar to the findings using the *Top10Bank* reputation measure (Table 4, Panel B). An increase in any one of the four report traits, *Optimism*, *Boldness*, *ReportPiggybacking*, or *NewsPiggybacking*, has a significantly negative impact on analysts' careers. Each of these findings agrees with the investment bank monitoring hypothesis.

The career impacts are significantly more severe for analysts employed at a *Top25Bank* than at another financial service firm. This reinforces the basic finding that the more reputable banks exert greater control over their analysts, disciplining them more severely for misleading reports. This result is confirmed in six separate tests using each of the different traits, both for the earnings forecasts and for the stock recommendations (Table 4, Panel B). In all six test estimations, both forecast *Accuracy* and *Experience* have significantly positive impacts on careers, as predicted by Clement (1999), Mikhail et al. (1999), Hong et al. (2000), Clement and Tse (2003), and Hong and Kubik (2003).

We test the bank reputation hypothesis further using the *CMLRBank* binary measure. This third measure is built following the Carter and Manaster (1990) underwriting tombstone status reputation measure, with updates from Loughran and Ritter (2004). Due to the discontinuity in the ranking that underlies this reputation method, it does not allow identifying a set of *Top10Bank*s.

Again, in each of the six tests, the bank employers punish the analysts' careers for misleading reporting. This agrees with bank oversight of their analysts and their reports. Moreover, in each regression, the negative career impacts are significantly more severe at the most reputable banks than at the less reputable banks. Also, in all estimations both forecast *Accuracy* and *Experience* have significantly positive impacts on careers (Table 4, Panel C). Together, the results using each of the three different bank reputation measures, for both analysts' earnings forecasts and their stock recommendations, are consistent with bank employers being associated with control and discipline over their analysts, imposing worse career outcomes for their analysts who produce more biased reports or more shirking reports.

Furthermore, the evidence is consistent with banks using their reputation to bond their security analysts' research. In particular, the disciplining of the analysts employed by the most reputable banks is more severe than at the other banks. This agrees with the idea that reputable banks protect their valuable reputations more when they are threatened to assure credible reporting by their analysts. The evidence is consistent with the banks being aware of their analyst behavior and actively monitoring and managing their use of bias and shirking, and consistently punishing those who are biased or shirking by shortening their careers and not promoting them. That the top banks invest significantly more in these monitoring activities agrees with protecting and furthering their more valued reputations, and thus future cash flows, in the financial markets.

5.6 A perspective from estimated elasticities

Further insight into the sensitivity of analysts' careers to bias and to shirking is provided by career shifts with respect to change in each trait, estimated using Table 4 coefficients, for analysts at the top banks and at the bottom banks, using Greene's method (2011, Chapter 10). The elasticities are estimated for two of the more interesting levels of the dependent variable: demotions and promotions, for the forecasts sample and for the recommendations sample. To numerically illustrate the effects, we consider the career response to a 25% increase in the respective trait. Note the comparisons between top banks and bottom banks are based on the statistically significantly different coefficient estimates reported in Table 4.

First is bias elasticity. The estimates show a 25% increase in *Optimism* raises the likelihood of demoting the analyst by 17% at top banks and by 13% at bottom banks (Table 5, Panel A) and reduces analysts' chances for promotion by 26% at top banks and by 20% at bottom banks (Table 5, Panel B). For

Boldness, corresponding increases in demotions are 27% at top banks and 24% at bottom banks, while chances for promotion drop by 49% at top banks and 38% at bottom banks. These career elasticities are confirmed by the corresponding estimates for analysts' stock recommendation reports (Table 5, Panel A, Columns 4-6). Together, the elasticities show again that top banks discipline their analysts more severely than bottom banks. Note however, both types of banks discipline their analysts, further agreeing with the bank monitoring and bank reputation hypotheses.

[Insert Table 5 about here]

The elasticity of career responses to the shirking traits, *NewsPiggybacking* and *ReportPiggybacking*, is highly significant. It is also greater at the top banks than at the bottom banks for both earnings forecasts and stock recommendations (Table 5 Panels A and B). Top banks are more likely to demote and less likely to promote shirking analysts than bottom banks.

Bias elasticities are significantly larger for *Boldness* than for *Optimism* and the shirking elasticities are greater for *NewsPiggybacking* than *ReportPiggybacking*. This is again the same at both top banks and bottom banks. Additionally, the career elasticities are stronger for earnings forecasts than stock recommendations.

6. Expectations management hypothesis

That analysts are rewarded with better careers when their reports are more accurate, less optimistic and less bold, is consistent with the investment bank monitoring hypothesis. However, the same findings also agree with what we call the "Expectations management hypothesis": Analysts' careers are better because their reports converge with managements' guidance, endorsing an earnings target that management can meet and beat (Cotter et al. 2006; Bhojraj, et al. 2009; He and Tian 2013; Doyle, et al. 2013; Heflin, et al., 2016). This literature suggests an analyst will issue a rather optimistic first quarterly earnings forecast, then subsequently revises her forecast down to a level that management can meet or beat, which is signaled initially by the managements' guidance. It is thus the case that analysts' reports that are involved in the earnings guidance game are not really in clients' interests. We evaluate the conflicting predictions of the expectations management hypothesis and the monitoring hypothesis, using three tests.

6.1 Proximate forecasts

The expectations management hypothesis suggests that better careers are likely for analysts who more often use forecasts that are more proximate with management guidance. While a neutral analyst may not strive to meet management's guidance, those seeking reward and recognition from management are likely to respond more promptly to management's earnings guidance, on average. This proximity hypothesis is tested twice, once using analysts' forecasts and once using their recommendations. *Proximity* is the average number of days between an analyst's report and the latest management guidance across all forecasts/stock recommendations issued by the analyst during the year, where lower values of *Proximity* represent more proximate reports.

Analysts with more proximate forecasts typically do not have better career outcomes, on average (Table 6, Panel A, Column 1). The negative impact of quicker report responses (hence lower *Proximity*) on careers is similar for analysts employed at a *TopBank* and a *BottomBank* (Table 6, Panel A, Column 2). Qualitatively similar proximity results are found using stock recommendations (Table 6, Panel A, Columns 4).

The findings from the proximity tests therefore agree with the monitoring hypothesis, as analysts with reports that respond more quickly to management guidance have worse career outcomes, contradicting the expectations management hypothesis. This result is the same for top and for bottom banks.

[Insert Table 6 about here]

6.2 Penny tests

A second test of the earnings management hypothesis uses what we call the penny tests. The "one penny test" examines how the frequency with which analysts' latest quarterly forecasts are off by exactly one penny from the latest management guidance, thus impacting their career outcomes, while controlling for their absolute forecast errors. If analysts tend to be rewarded for closely following guidance, then we expect better career outcomes for those who track guidance more slavishly.

Diligently following guidance, in particular staying within one penny of guidance, does not have a positive impact on careers, contrary to the guidance hypothesis (Table 6, Panel A, Column 5). Moreover, the impacts for analysts employed by the more reputable banks are worse (Table 6, Panel A, Column 6).

Results from a second similar test using the analysts who stay within two pennies of earnings support the same conclusion (Table 6, Panel A, Columns 7 and 8). They show top banks punish more severely. Further unreported results using a nickel filter also fully agree with these findings. Absolute *Forecast Error* is largely insignificant, confirming the finding by Mikhail et al. (1999) that it is relative, not absolute, accuracy that matters to analysts.

6.3 A look at long-term forecasts

The third test of the expectations management hypothesis examines long-term forecasts to gauge how analysts' long-term accuracy, optimism and boldness impact their careers. The expectations management literature focuses on guiding myopic analysts' short-term forecasts (Bhojraj, et al. 2009; Feng and McVay 2010; He and Tian 2013; Bradshaw, et al. 2016). Thus, if the above positive association between analysts' *Accuracy*, *Boldness*, and *Optimism* with career outcomes is driven by analysts' following management's near-term earnings guidance, then such positive associations should not be evident in the case of long-term earnings forecasts, all else the same. In contrast, both the monitoring hypothesis and the reputation hypothesis suggest that more *Accuracy*, less *Boldness*, and less *Optimism* for long-term forecasts will positively impact analysts' careers. To conduct these tests we concentrate on the latest two-year ahead annual forecasts. We then calculate *Accuracy*, *Optimism*, and *Boldness* measures following the same procedure used for the quarterly forecasts in our main analysis.

The results of the third test of the expectations management hypothesis show that *Accuracy* has a positive career impact, while *Optimism* has a negative career impact for two-year forecasts (Table 6, Panel B, Column 1). Furthermore, these career impacts are slightly greater for the analysts who are employed at the more reputable banks (Table 6, Panel B, Column 2). For the case of *Boldness*, the two-year forecasts have a significantly negative impact on careers and it is significantly stronger at more reputable banks (Table 6, Panel B, Columns 3 and 4).

One more test of long-term earnings hypothesis looks at one-year ahead forecasts, a second long-term earnings measure, to assess the impacts of *Accuracy*, *Optimism*, and *Boldness* on careers. The test of the one-year forecasts show both *Accuracy* and *Experience* have a positive impact on careers, and both *Optimism* and *Boldness* have significant negative impacts (Table 6, Panel B, Columns 5 and 7). Moreover, these impacts are significantly stronger at the more reputable banks (Table 6, Panel B, Columns 6 and 8).

The findings from each of several tests reject the expectations management hypothesis. They agree with the monitoring hypothesis and the reputation hypothesis.

7. Robustness

Thus far the findings have generally been free of concern for the type of analysts' reports, either earnings forecasts or stock recommendations and have been robust to alternate measures of bank reputation. Moreover, the findings are confirmed in tests using respective bias traits: *Optimism* and *Boldness*, and shirking traits: *NewsPiggybacking* than *ReportPiggybacking*. The regression tests control for two classic determinants of analysts' reports, *Accuracy* and *Experience*, as well as for both year and employer fixed effects. In unreported tests, we confirm the results for the Shorter Sample that begins in 2003 (see Appendix A) after the Global Settlement. These findings are qualitatively the same as the results reported herein.

Here we examine a range of variations of the regression tests of the monitoring and reputation hypotheses.

7.1 Four career levels

One concern is with the sensitivity of the findings to alternative specifications of the dependent variable in the ordered Probit model regressions. There are three career outcomes in this specification:

moving up to a higher position, moving down to a lower position, and departing from the profession. One alternative specification is to have four outcomes which allows further distinguishing of departures from demotions. Results from this four outcome Probit regression are reported in Table 7.

[Insert Table 7 about here]

The estimates obtained with the four-outcome specification of the Probit regression models (Table 7, Panel A) are virtually identical to the estimates using the three-outcome specification (Table 4). This is the case for each of the three different measures for bank reputation (Table 7, Panels A, B and C) for all four report traits, and for both earnings forecasts and stock recommendations.

In all estimations, punishment for bias and shirking is more severe at the top banks, whether measured by the *Top10Bank*s, the *Top25Bank*s, or using the CMLR banks (Table 7). This is consistent with the reputation hypothesis.

7.2 Another measure for career outcomes: Up, Down, and *Depart*

A third way to assess the career responses to bias and shirking behavior is to examine three separate Probit regressions, one for each of the three discrete outcomes: moving up to a higher decile bank, moving down to a lower decile bank, and leaving the profession (stop issuing reports on I/B/E/S). For each analyst during year $t + 1$, the corresponding binary variable is one when the indicated job switch occurs, and zero otherwise.

Table 8 reports the Probit estimation results for the probabilities of moving *Up*, *Down*, and to *Depart*. Because analysts employed by investment banks in the highest (lowest) decile cannot move up (down), this decile is excluded from the *Up* (*Down*) Probit regressions. Panels A and B report the results for both bias traits using earnings forecasts. Panel C and D report the results for all four traits, for both forecasts and recommendations. We recognize that movements down are a noisy measure because analysts may start their careers at the top investment banks and subsequently move to smaller local brokerage firms that may be associated with better career outcomes (higher salaries and internal promotions, etc.). Finally, although Mikhail et al. (1999) and Hong et al. (2000) argue that "the possibility that an analyst may have left for a better job such as a fund manager after leaving the I/B/E/S sample is remote" (Hong et al. 2000, p. 125), some analysts who depart the profession may switch to the buy side (Cen et al. 2018).

[Insert Table 8 about here]

Consider first the results using earnings forecast reports. These results focus on analysts' bias measured with *Optimism* and then *Boldness*. Table 8 Panel A estimates demonstrate that when analysts move up, all banks are less inclined to promote their optimistic analysts. Additionally, optimistic analysts at the top banks are significantly less likely make a career move up to a more reputable bank. Moreover, both top and bottom banks demote their optimistic analysts down. In addition, optimistic analysts face a higher likelihood of departure, and this is particularly stronger at the top banks.

A somewhat similar pattern emerges for *Boldness*, shown in Panel B. The *TopBanks* discriminate against moving their bolder analysts up, they are significantly more likely to move their bolder analysts down, and their bolder analysts are significantly more likely to depart.

The results from further tests using the shirking traits in Panels C and D are qualitatively similar. The banks are less inclined to move shirking analysts up, their shirking analysts are more likely to move down, and those analysts are more likely to depart; this holds for both the *ReportPiggybacking* analysts (Panel C) and the *NewsPiggybacking* analysts (Panel D). Moreover, shirking analysts at the top banks and bottom banks are significantly more likely to depart, whether they report piggybacking or news piggybacking (Panels C and D). The forecast results are confirmed by the stock recommendation findings (Table 8, Columns 4, 5, and 6, Panels C and D).

There are two general takeaways from these findings that pertain to analysts who use biased and shirking reports. First, these analysts are punished; they are less likely to move up, are more likely to move down, and they are also more likely to depart. This agrees with the monitoring hypothesis. Second, these impacts on analysts are significantly stronger at the top banks in the sample. These inferences are corroborated for each of the four traits, for both the earnings forecasts and the stock recommendation reports. They agree with the reputation hypothesis

Note also that analysts with greater accuracy do not face a greater likelihood of *Up*, but they are less likely to be punished with a *Down* or a *Depart* move. In addition, more *Experience* reduces the likelihood of any career change. These findings are common across all four traits and for both kinds of reports.

7.3 Multiple traits

The career regression tests have focused on one trait at a time, either for bias or for shirking. This method follows the suggestion of theoretical econometricians to avoid mechanical multicollinearity that can arise when using binary interaction variables (Belsley et al. 1980; Greene, 2011, p. 60).[16] However, for robustness, here we report the estimations when jointly using two proxies at a time, one for bias and one for shirking, in the same regression; first the *Optimism* measure of bias with *NewsPiggybacking* then with *ReportPiggybacking*, and then the same for the *Boldness* measure of bias.

[Insert Table 9 about here]

Consider first including *Optimism* and *ReportPiggybacking* (Table 9, Panel A). First, both *Optimism* and *ReportPiggybacking* have significantly negative impacts on careers (Column 1), consistent with the monitoring hypothesis. The same monitoring effect is present when including the interactive *TopBank* and *BottomBank* dummies. The discipline for optimistic forecasting and for *ReportPiggybacking* is significantly more severe at the top banks than at the bottom banks (Column 2).

A similar pattern arises when considering *Optimism* with *NewsPiggybacking*; *Optimism* has a more negative impact at the more reputable banks (Col. 3 and 4). For news piggybacking the results are similar, and the punishment is more severe at the Top Banks.

Using the second proxy for bias, *Boldness*, provides further evidence that agrees with the monitoring hypothesis and the bank reputation hypothesis. *Boldness* has a negative impact on careers, and

[16] Testing for the collinearity issue from interactions with *TopBank* and *BottomBank* dummies, shows the Condition Number is over 20, and the correlation coefficients are around 0.9, indicative of serious collinearity.

significantly more so at the Top Banks (Panel B, Col. 1 and 2). *ReportPiggybacking* likewise is harmful for analysts' careers, and more so at Top Banks (Panel B, Col. 1 and 2).

The pattern is the same using both *NewsPiggybacking* and *Boldness* in the same regression; more of either is punished, and more so at Top Banks (Panel B, Col. 3 and 4).

Together, the results when using both a bias and shirking proxies in the same regressions confirm the findings in the simpler case of one proxy at a time. The banks monitor their analysts, punishing those who tend to issue more biased and more shirking reports, and the disciplining of the analysts employed by the most reputable banks is more severe than at the other banks. This agrees with the Top Banks protecting their more valuable reputations more when they are on the line, to assure credible reporting by their analysts. It agrees with the banks being aware of their analyst behavior and actively monitoring and managing their use of bias and shirking, and consistently punishing those who are biased or shirking by shortening their careers and by not promoting them. The notion that the top banks invest significantly more in these monitoring activities agrees with protecting their more valued reputations and thus give them competitive access to better future cash flows. Note including two proxies for bias or two proxies for shirking in the same regression model is redundant, as each pair proxies for the same the type.

7.4 Do personal reputations deliver enough bonding for analysts?

A natural question arises concerning whether analysts' have sufficient personal reputations to bond their own research, thus dismissing the role of the banks' reputations in monitoring analysts. Authors measure analysts' personal reputations by the possession of the *Institutional Investor Award*, or *II Award*, and they report mixed findings (Emery and Li, 2009; Fang and Yasuda, 2009; Maber et al. 2014).

Our findings show the *II Award* is not capable of credibly bonding the reports of typical analysts. The typical analyst's odds of winning the *II Award*, adjusted for the odds of staying in the profession, are just too low, below 1% on average, as relatively too few analysts have a reasonable shot at winning the *Award* (Table 10). The typical analysts' chance of winning a first *II Award* is around 1% at a *Top10Bank* and much less at all of the other banks.

The *II Award* is generally available only to a very small fraction of the entire analyst population. For example, it is not plausibly available over the first five career years for the vast majority of analysts, nor to almost any analyst who is not employed at a *Top10Bank*. In general, because the mean likelihood of winning a first *II Award* is quite small, market participants know the typical analyst can expect very little wealth from winning an *II Award*, which cannot bond her reports. Consequently, the *II Award* is unable to bond the typical analyst because the expected wealth it puts on the line, is unlikely to exceed the analyst's possible gains from biasing her reports, shirking, and violating clients' trust. The expected personal reputation value from winning the *II Award* is therefore too little to certify the reports from most analysts.

[Insert Table 10 about here]

8. Conclusion

This article investigates the influence of investment banks on their analysts' reporting behavior, following the Global Settlement and contemporary reforms in the early 2000s. In this period investment banks are the major employers of analysts and they have more than doubled the supply of analysts' research reports.

After controlling for forecast accuracy and analysts' experience, relevant career factors established in the literature, new findings show that both biased reporting and shirking reporting are linked to worse career outcomes. The results are confirmed using two proxies for bias, optimistic reports and bold reports, and using two proxies for shirking, report piggybacking and news piggybacking. The findings agree with the hypothesis that banks monitor and discipline their security analysts.

Further results show that discipline is significantly greater for analysts who are employed at the most reputable banks. Analysts employed at more reputable banks who issue more optimistic reports, or bolder reports, or report piggybacking reports, or news piggybacking reports, are likely to have shorter careers than other analysts who do not use these reports. These findings support the view that investment banks, as employers of analysts, put their reputations on the line in the capital markets to bond the reliability of their analysts' reports, providing a mechanism for resolving analysts' moral hazard. We conclude overall that misleading reporting is detrimental to security analysts' career concerns, because of discipline from their investment bank employers.

Further analyses of analysts' personal reputations confirm the unique importance of bank reputation for validating analysts' reports and resolving their moral hazard problems. For typical analysts the odds of winning an *II Award* are too low, often below one percent. Consequently, the securities market cannot rely on analysts' expected personal reputation prospects to bond the reliability of their reports.

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Appendix A

Sample descriptions.

Full Sample	Forecast revisions and recommendation changes are collected from the 2001-2014 I/B/E/S Detail file for U.S. firms. This sample yields 15,944,846 forecasts and 595,335 recommendations, showing that the forecast is the most sought after type of analyst report (Altınkılıç et al. 2013). A total of 17,213 analysts issue forecasts and 15,379 analysts issue recommendations in the sample. Each forecast and each recommendation is classified as an upgrade or a downgrade. If the current value of the forecast is above (below) the outstanding value from the same analyst for the same company and fiscal period, the report is an upgrade (downgrade). For recommendation changes on I/B/E/S, coded 1 through 5 (strong buy to sell), the sign is reversed because the most favorable change has the lowest value.
Shorter Sample	This sample is the Full Sample for the shorter period of 2003-2014 following the Global Settlement.

Appendix B

Definitions of terms and variables.

Accuracy	Computed following Mikhail et al. (1999). To compute relative *Accuracy*, all analysts following the firm during year t are ranked based on their $Error_{i,j,t}$, $Error_{i,j,t} = (F_{i,j,t} - E_{j,t}) \div p_{-5}$, where $F_{i,j,t}$ is analyst's i's forecast for company j earnings during year t, $E_{j,t}$ is the firm's actual earnings during year t, and p_{-5} is the CRSP stock price 5 days before the forecast. *Accuracy* is relative to that of all other analysts with the same primary industry following the same firm during year t. These n comparison analysts, which could be employed at the same employer, must have the same primary industry and have issued at least one forecast for each quarter of the year for the firm for which they serve as a comparison group. Only firms that are followed by five or more analysts are included. All n analysts are ranked based on their accuracy in a given year, where the most accurate analyst rank is n, then we divide this rank by n, so rank ranges from $1/n$ to 1, with high levels corresponding to relatively more accurate analysts, and represents analyst i's accuracy rank for firm j and year t relative to his cohort analysts. The rank Accuracy statistic for analyst i and year t is her average rank for the year.
Bias	Refers to both *Optimism* and *Boldness*.
Boldness	Computed following Hong et al. (2000). For each firm in each year, all analysts covering a firm are ranked by how much they deviate from the consensus forecast of that year (the boldest analyst receives the first rank, the second-boldest the second rank, etc.). From these rankings, each analyst gets a *Boldness* score for each stock in her coverage portfolio. For each analyst then calculate her overall forecast *Boldness* score which is the average of her analyst's *Boldness* scores in year t.
BottomBank	A binary variable equal to 1 – *TopBank*.
Career	The unobserved continuous random variable $Career^{*}_{i,d}$, has M discrete job switch categories. For example, the analyst could move up, does not move, move within the same decile, or move down including leaving the profession. We would therefore observe the M categories (in the example, $M = 3$): leave the profession or move down to a lower decile investment bank (lowest category), remain at the same investment bank or move to a bank within the same decile (middle category), and move up to a higher decile investment bank (highest category). The job switches are across investment bank deciles, formed by sorting the banks each year by the number of analysts employed. A switch to a higher (lower) decile, hence to a more (less) reputable bank, is a good (bad) career outcome. Thus, suppose there are $M + 1$ real numbers, $\mu_0, \mu_1, ..., \mu_M$, where $\mu_0 = -\infty$, $\mu_1 = 0$, ..., $\mu_M = \infty$, and $\mu_0 \le \mu_1 \le ... \le \mu_M$. Then define $R_{i,j} = \mu_j - x_i$. The probability that the unobserved dependent variable is contained in the i[th] category is then written as $\Pr[\mu_{j-1} < Career^{*} < \mu_j] = \Phi(R_{i,j}) - \Phi(R_{i,j-1})$.
CMLR banks	Investment bank reputation using the Carter and Manaster (1990) underwriting tombstone status reputation measure, with updates from Loughran and Ritter (2004).
Depart	Binary variable equal to one if the analyst is in I/B/E/S database in year t, but not in year t+1.
Down	Binary variable equal to one for moving down to an employer assigned to a lower decile based on the number of employed analysts.
Downgrade	A binary variable equal to one if the current value of the forecast is below the outstanding value from the same analyst and company and fiscal period. For recommendation changes from I/B/E/S, coded 1 through 5 (strong buy to sell), the sign is reversed because the most favorable change has the lowest value.

(cont.)

Appendix B (continued)

Earnings announcements	Taken from I/B/E/S.
Experience	Computed following Mikhail et al. (1999). The number of years the analyst has been in the database by year t.
Forecast Error	$Error_{i,j,t}$, $Error_{i,d} = \lvert F_{i,j,t} - E_{j,t} \rvert \div p_{-5}$, where $F_{i,j,t}$ is analyst's i's forecast for company j earnings during year t, $E_{j,t}$ is the firm's actual earnings during year t, and p_{-5} is the CRSP stock price 5 days before the forecast. For each analyst i during year t, *Forecast Error* is the mean value for $Error_{i,j,t}$ across all firms in the analyst's main industry.
II Award	A dummy variable that equals one if the analyst has been on *Institutional Investor's All-America* ranking (any ranking) at least once by year *t*.
Intercept2 (3)	The second (third) intercept threshold for the ordinal Probit regression with three (four) levels of the dependent variable.
Key event	Is an earnings announcements or Company Issued Guidance.
Large return	A large return is a daily return that is more than two standard deviations away from the mean. The means and the standard deviations are calculated annually.
Long-term forecasts	These are analysts' forecasts one-year ahead and two-year ahead earnings.
NewsPiggybacking	Computed following Altınkılıç et al. (2013), but computed here at the analyst level. A forecast (recommendation) is piggybacking on news if it follows a key event or a large return within 3 days. *NewsPiggybacking* for analyst i during year t is the fraction of all forecasts (recommendations) piggybacking on news.
One Penny	For each latest quarterly forecast, a binary variable is created which equals one if the forecast is within one penny from the latest management guidance for the same quarter, and zero otherwise. For analyst i during year t, One Penny is the average of such binary variables across all latest quarterly forecasts.
Optimism	Computed following Hong and Kubik (2003). The fraction of all forecasts issued by analyst during year t that are above the consensus.
Proximity	Proximity is the average number of days between an analyst's report and the latest management guidance across all forecasts/stock recommendations issued by the analyst during the year.
Recommendation ratings	The recommendation is coded from 1 (strong buy) to 5 (strong sell). Recommendations are from I/B/E/S U.S. 2001-2014.
ReportPiggybacking	Computed following Altınkılıç et al. (2013), but computed here at the analyst level. A forecast (recommendation) is piggybacking on another report if it follows a forecast (recommendation) of another analyst within 3 days. *ReportPiggybacking* for analyst i during year t is the fraction of all forecasts (recommendations) piggybacking on another report.
Shirking	Refers to both *ReportPiggybacking* and *NewsPiggybacking.*
TopBank	Either *Top10Bank, Top25Bank, Top 11-25 Bank*, or *CMLR Bank,* depending on the test.
Top 10 Bank	A binary variable equal to one if the analyst i during year t is employed by a top 10 bank, measured by the total number of employed analysts.
Top 11-25 Bank	A binary variable equal to one if the analyst i during year t is employed by a top 11-25 bank, measured by the total number of employed analysts.
Top 25 Bank	A binary variable equal to one if the analyst i during year t is employed by a top 25 bank, measured by the total number of employed analysts.
Trait	A general term that refers to one of the bias or shirking traits, like *Boldness*, *ReportPiggybacking*, etc.
# PENNIES	For each latest quarterly forecast, a binary variable is created which equals one if the forecast is within # = 1 (# = 2) pennies from the latest management guidance for the same quarter, and zero otherwise. For analyst i during year t, *# PENNIES* is the average of such binary variables across all latest quarterly forecasts.
Up	Binary variable equal to one for moving up to an employer assigned to a higher decile based on the number of employed analysts.
Upgrade	If the current value of the forecast is above the outstanding value from the same analyst and company and fiscal period, the forecast is an upgrade. For recommendation changes from I/B/E/S, coded 1 through 5 (strong buy to sell), the sign is reversed because the most favorable change has the lowest value.

Figure 1 A

Boldness versus *Optimism*. Deciles based on *Optimism* are on the horizontal axis and average values for *Boldness* are on the vertical axis.

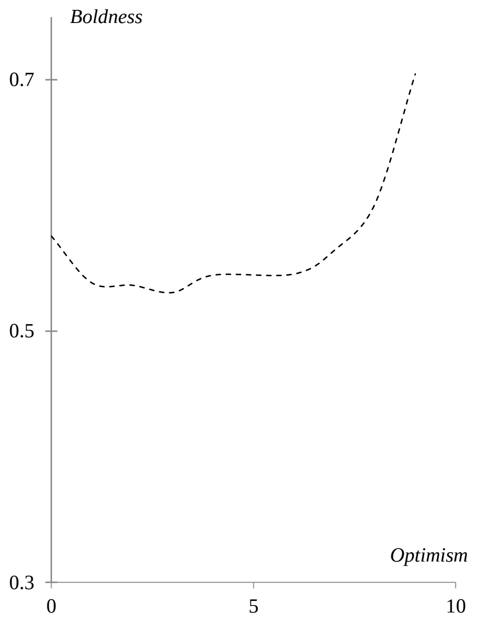

Figure 1 B

ReportPiggybacking versus *NewsPiggybacking*. Deciles based on *NewsPiggybacking* are on the horizontal axis and average values for *ReportPiggybacking* are on the vertical axis.

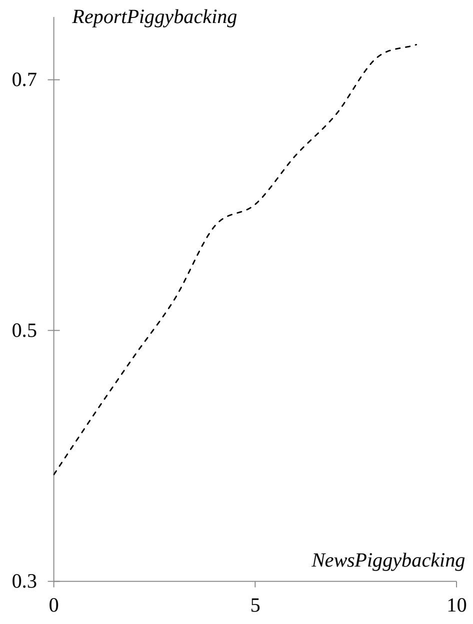

Table 1
Analyst report frequencies.

Intraday breakdown	Forecast time of day		
	All	Day	Night
Panel A. Analysts' forecasts			
Sample size (N)	15,944,846	6,311,245	9,633,601
Analyst-year observations (N)	74,914	65,500	68,861
N reporting analysts (N)	17,213	15,115	15,954
Upgrades (%)	43.94	43.68	44.10
Downgrades (%)	53.28	53.40	53.21
Panel B. Analysts' recommendations			
Sample size (N)	595,335	269,833	325,502
Analyst-year observations (N)	65,467	45,671	54,808
N reporting analysts (N)	15,379	11,993	13,585
Upgrades (%)	34.56	34.58	34.54
Downgrades (%)	42.86	44.59	41.49

Descriptive statistics for all forecasts and recommendations by their daytime or nighttime occurrence. The Full Sample is described in Appendix A.

Table 2
30 largest analysts' employers and other analyst employers.

*Panel A. Top 30 analyst employers; No. analysts employed yearly by investment banks and financial service firms (noted by *)*

Employer	No.	% of top 30	Sum	Employer	No.	% of top 30	Sum
Merrill Lynch	251	10.5%	10.5%	CIBC World Markets	58	2.4%	71.4%
Deutsche Banc Alex Brown	150	6.3	16.8	Wachovia Securities	55	2.3	73.7
Citigroup	146	6.1	22.9	A.G. Edwards & Sons	54	2.3	75.9
UBS Warburg	138	5.8	28.7	Sidoti & Co. LLC*	53	2.3	78.2
Morgan Stanley	133	5.6	34.3	Robertson Stephens	51	2.1	80.3
Goldman Sachs	122	5.1	39.5	Prudential Equity Group	50	2.1	82.5
J.P. Morgan	119	4.9	44.4	Standard & Poors Corp.*	50	2.1	84.6
Credit Suisse	118	5.0	49.4	Paine Webber Inc.	49	2.0	86.6
Bear, Stearns & Co.	79	3.3	52.6	HSBC Securities	48	2.0	88.6
Raymond James & Assoc.	67	2.9	55.5	BMO Cap. Markets Corp.*	48	2.0	90.6
Salomon Brothers	66	2.8	58.3	Kidder, Peabody & Co. Inc.	47	2.0	92.6
RBC Capital Markets	65	2.8	61.0	Natwest Securities Corp.	47	2.0	94.6
U.S. Bancorp Piper Jaffray	65	2.6	63.7	Jefferies & Co.	45	1.9	96.5
Banc of America Securities	64	2.8	66.4	Friedman, Billings, Ramsey	43	1.8	98.2
DLJ Securities	62	2.6	69.0	Stifle, Nicolaus & Co.	42	1.8	100.0

Panel B. Other analyst employers

No. employers	No. analysts employed per year	No. employers	No. analysts employed per year	No. employers	No. analysts employed per year
34	from 15 to 24	116	from 5 to 9	114	2
42	from 10 to 14	117	from 3 to 4	256	1

Panel C. Analyst job switching

Year	Total analysts	Up	Down	Depart	Enter
2000	4,099	239	117	988	776
2001	4,100	207	182	1,107	989
2002	4,047	75	140	1,192	1,054
2003	4,259	75	155	1,360	1,404
2004	4,196	116	118	1,196	1,297
2005	4,005	107	155	891	1,005
2006	4,051	99	115	906	937
2007	4,066	116	96	920	921
2008	4,133	66	186	938	987
2009	4,042	55	184	1,069	847
2010	3,774	120	103	756	801
2011	4,392	136	128	549	1,374
2012	4,604	90	105	726	761
2013	4,547	60	127	823	669
Average	4,165	112	137	959	987

Average annual number of analysts employed are from I/B/E/S, and their percentages, including cumulative percentages for all employers and for the investment bank employers. Panels B and C report number of analysts' reports by employer class, and the mean number of reports by the employing bank. Missing are analysts employed at Lehman Brothers and at Merrill Lynch before the financial crisis, as I/B/E/S removed their data from its files.

Table 3
Probit regressions of analyst job switching across career deciles.

Panel A. Forecasts

		Analyst Trait			
Report type	No trait	Bias		Shirking	
Proxy trait		*Optimism*	*Boldness*	*Report-Piggybacking*	*News-Piggybacking*
Variable	(1)	(2)	(3)	(4)	(5)
Intercept	-2.99***	-2.76***	-2.11***	-2.84***	-2.78***
Intercept2	0.07	0.33	1.00***	0.22	0.29
Accuracy	1.19***	1.30***	0.71***	1.19***	1.19***
Experience	0.02***	0.02***	0.01***	0.02***	0.02***
Trait		-0.75***	-1.20***	-0.26***	-0.35***
N	24,049	24,049	24,049	24,049	24,049
Panel B. Recommendations					
Intercept	-2.99***			-2.95***	-2.85***
Intercept2	0.07			0.18	0.29
Accuracy	1.19***			1.05***	1.05***
Experience	0.02***			0.01***	0.01***
Trait				-0.10*	-0.23***
N	24,049			22,184	22,184

The dependent variable has three levels: move up to an employer in a higher decile based on the number of employed analysts (highest), no change or change within the same decile (middle), and move down or leave the profession (lowest). Deciles 1 and 10 are excluded from the regressions. The Full Sample is described in Appendix A. See Appendix B for variable descriptions. *** (**, *) Two-tail test indicates significantly different from 0 at the 1% (5%, 10%) level. Year and employer fixed effects are used in each regression and standard errors are adjusted for clustering along two dimensions; analyst and main followed industry, following Thompson (2011).

Table 4
Probit regressions of analyst switching across career deciles.

Panel A. Uses top 10 banks for TopBank

Analyst report	Forecasts				Recommendations	
Bias trait and Shirking trait	*Optimism*	*Boldness*	*Report-Piggybacking*	*News-Piggybacking*	*Report-Piggybacking*	*News-Piggybacking*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-2.76***	-2.13***	-2.86***	-2.81***	-2.96***	-2.86***
Intercept2	0.32	0.98***	0.21	0.25	0.18	0.28
Accuracy	1.30***	0.71***	1.19***	1.18***	1.05***	1.05***
Experience	0.02***	0.01***	0.02***	0.02***	0.01***	0.01***
Trait x TopBank	-0.82^{***,3}	-1.33^{***,2}	-0.32^{***,2}	-0.46^{***,1}	-0.19^{**,2}	-0.29^{***,2}
Trait x BottomBank	-0.71***	-1.15***	-0.23***	-0.30***	-0.05	-0.20***
N	24,049	24,049	24,049	24,049	22,184	22,184

Panel B. Uses top 25 banks for TopBank

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-2.80***	-2.19***	-2.90***	-2.88***	-2.97***	-2.88***
Intercept2	0.29	0.92***	0.16	0.19	0.16	0.25
Accuracy	1.30***	0.72***	1.19***	1.19***	1.05***	1.05***
Experience	0.02***	0.01***	0.02***	0.02***	0.01***	0.01***
Trait x TopBank	-0.83^{***,1}	-1.33^{***,1}	-0.33^{***,1}	-0.46^{***,1}	-0.18^{***,2}	-0.28^{***,2}
Trait x BottomBank	-0.66***	-1.06***	-0.17**	-0.21***	-0.02	-0.16***
N	24,049	24,049	24,049	24,049	22,184	22,184

Panel C. Uses top CMLR banks for TopBank

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-2.76***	-2.13***	-2.83***	-2.80***	-2.95***	-2.84***
Intercept2	0.32	0.98***	0.23	0.26	0.18	0.30
Accuracy	1.30***	0.72***	1.19***	1.19***	1.05***	1.05***
Experience	0.02***	0.01***	0.02***	0.02***	0.01***	0.01***
Trait x TopBank	-0.82^{***,3}	-1.33^{***,1}	-0.32^{***,2}	-0.42^{***,1}	-0.15^{**,2}	-0.25^{***,2}
Trait x BottomBank	-0.71***	-1.15***	-0.23***	-0.32***	-0.07	-0.17**
N	24,049	24,049	24,049	24,049	22,184	22,184

The dependent variable's four levels are move up to an employer in a higher decile based on the number of employed analysts (highest), no change or change within the same decile (middle), move down (low), and leave the profession (lowest). Deciles 1 and 10 are excluded from the regressions. The Full Sample is described in Appendix A. See Appendix B for variable descriptions. *** (**, *) Two-tail test indicates significantly different from 0 at the 1% (5%, 10%) level. ^{1} (^{2}, ^{3}) One-tail test indicates for each trait, *TopBank* coefficient estimate is significantly less than *BottomBank* coefficient estimate, at the 1% (5%, 10%) level. Year and employer fixed effects are used in each regression and standard errors are adjusted for clustering along two dimensions; analyst and main followed industry, following Thompson (2011).

Table 5
Elasticity estimates of analyst trait impacts on promotions and demotions or departures.

Analyst report	Forecasts			Stock recommendations		
Bank kind	*TopBank*	*BottomBank*	Difference	*TopBank*	*BottomBank*	Difference
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Level 1: Demotions or Departures						
Optimism	17.2%	12.5%	4.7%***			
Boldness	26.9%	23.8%	3.1%***			
ReportPiggybacking	7.8%	1.8%	6.0%***	4.2%	0.4%	3.8%***
NewsPiggybacking	8.7%	2.5%	6.2%***	6.5%	0.5%	6.0%***
Panel B. Level 3: Promotions						
Optimism	-26.0%	-19.8%	-6.2%***			
Boldness	-48.9%	-38.4%	-10.5%***			
ReportPiggybacking	-13.3%	-7.8%	-5.5%***	-5.1%	-0.6%	-4.5%***
NewsPiggybacking	-17.1%	-8.2%	-8.9%***	-8.6%	-0.1%	-8.5%***

The percentage career change is estimated from the implied elasticities from the Probit regressions of Table 4, measured at the means of the respective dependent and independent variables, for a 25% increase in the respective trait. Uses *Top10Bank*s for *TopBanks*. The Full Sample is described in Appendix A. See Appendix B for variable descriptions. *** (**, *) Two-tail test indicates significantly different from 0 at the 1% (5%, 10%) level. Year and employer fixed effects are used in each regression and standard errors are adjusted for clustering along two dimensions; analyst and main followed industry, following Thompson (2011).

Table 6

Expectations management hypothesis tests.

Panel A. Career impact of proximity of analysts' forecast with management forecasts, and analysts beating management forecasts by pennies

Test:	Proximity of analysts' reports to managements' forecasts				Tendency for management forecast to beat analysts' forecasts			
	Forecasts		Recommendations		*One penny*		*Two pennies*	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-3.01***	-3.01***	-2.92***	-2.92***	-2.93***	-2.94***	-2.96***	-2.96***
Intercept2	0.09	0.09	0.25	0.25	0.03	0.03	0.01	0.01
Accuracy	1.18***	1.18***	1.06***	1.05***	1.20***	1.20***	1.20***	1.20***
Experience	0.02***	0.02***	0.01***	0.01***	0.02***	0.02***	0.02***	0.02***
Proximity	0.46***		0.12***					
Proximity x TopBank		0.47***		0.10***				
Proximity x BottomBank		0.45***		0.13***				
# PENNIES					-0.06***		0.03	
# PENNIES x TopBank						-0.38^{***,1}		-0.30^{***,1}
# PENNIES x BottomBank						0.08		0.16*
Forecast Error	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	24,049	24,049	24,049	24,049	24,049	24,049	24,049	24,049

Panel B. Career impact of long-term forecast bias, Optimism and Boldness

Long term forecast:	Two-year				One-year			
Bias trait:	*Optimism*		*Boldness*		*Optimism*		*Boldness*	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-2.39***	-2.39***	-2.34***	-2.37***	-2.38***	-2.39***	-2.01***	-2.02***
Intercept2	0.90***	0.90**	0.95**	0.92***	0.64***	0.63***	1.03***	1.02***
Accuracy	-0.01	-0.01	-0.01	-0.01	0.29***	0.29***	0.26***	0.26***
Experience	0.01***	0.01***	0.01***	0.01***	0.02***	0.02***	0.02***	0.02***
Bias trait	-0.12***		-0.20***		-0.35***		-1.01***	
Bias trait x TopBank		-0.13**		-0.36^{***,1}		-0.41^{***,3}		-1.07^{***,2}
Bias trait x BottomBank		-0.11***		-0.13**		-0.33***		-0.98***
N	24,049	24,049	24,049	24,049	24,049	24,049	24,049	24,049

Panel A columns 1-4 examines how proximity of analysts' forecast with management forecast impacts analysts' careers. Panel A columns 5-8 examines how the frequency of analysts' quarterly forecast being beaten by one (two) penny, impacts careers. Panel B examines how analysts' long-term (two-year and one-year earnings) forecast bias, *Boldness* and *Optimism*, impacts careers. The Full Sample is described in Appendix A. See Appendix B for variable descriptions. *** (**, *) Two-tail test indicates significantly different from 0 at the 1% (5%, 10%) level. ^{1} (^{2}, ^{3}) One-tail test indicates for each trait, *TopBank* coefficient estimate is significantly less than *BottomBank* coefficient estimate, at the 1% (5%, 10%) level. Year and employer fixed effects are used in each regression and standard errors are adjusted for clustering along two dimensions; analyst and main followed industry, following Thompson (2011).

Table 7
Four level Probit regressions of four types of analyst job switches.

Panel A. Uses top 10 banks for TopBank

Analyst report	Earnings forecasts				Stock recommendations	
Bias trait and shirking trait	*Optimism*	*Boldness*	*Report-Piggybacking*	*News-Piggybacking*	*Report-Piggybacking*	*News-Piggybacking*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-2.71***	-2.06***	-2.81***	-2.78***	-2.92***	-2.82***
Intercept2	0.37*	1.06***	0.25	0.29	0.21	0.31
Intercept3	0.57***	1.26***	0.45**	0.49**	0.43*	0.53**
Accuracy	1.36***	0.75***	1.24***	1.24***	1.11***	1.11***
Experience	0.02***	0.02***	0.02***	0.02***	0.01***	0.01***
Trait x TopBank	-0.86^{***,2}	-1.40^{***,1}	-0.33^{***,2}	-0.46^{***,1}	-0.19^{***,1}	-0.30^{***,1}
Trait x BottomBank	-0.74***	-1.21***	-0.24***	-0.28***	-0.05	-0.21***
N	24,049	24,049	24,049	24,049	22,184	22,184
Panel B. Uses top 25 banks for TopBank						
Intercept	-2.74***	-2.11***	-2.85***	-2.84***	-2.94***	-2.85***
Intercept2	0.34	1.00***	0.21	0.22	0.19	0.29
Intercept3	0.54**	1.21***	0.41*	0.42*	0.41*	0.51**
Accuracy	1.36***	0.75***	1.24***	1.24***	1.11***	1.11***
Experience	0.02***	0.02***	0.02***	0.02***	0.01***	0.01***
Trait x TopBank	-0.85^{***,2}	-1.39^{***,1}	-0.34^{***,1}	-0.45^{***,1}	-0.19^{***,1}	-0.28^{***,2}
Trait x BottomBank	-0.70***	-1.12***	-0.19**	-0.20***	0.02	-0.17***
N	24,049	24,049	24,049	24,049	22,184	22,184
Panel C. Uses top CMLR banks for TopBank						
Intercept	-2.71***	-2.06***	-2.79***	-2.76***	-2.92***	-2.80***
Intercept2	0.37*	1.05***	0.27	0.30	0.21	0.33
Intercept3	0.58***	1.26***	0.47**	0.50**	0.43*	0.55**
Accuracy	1.36***	0.75***	1.24***	1.24***	1.11***	1.11***
Experience	0.02***	0.02***	0.02***	0.02***	0.01***	0.01***
Trait x TopBank	-0.86^{***,3}	-1.40^{***,1}	-0.32^{***,2}	-0.41^{***,2}	-0.16^{**,2}	-0.26^{***,2}
Trait x BottomBank	-0.76***	-1.21***	-0.24***	-0.31***	-0.07	-0.16***
N	24,049	24,049	24,049	24,049	22,184	22,184

The dependent variable's four levels are move up to an employer in a higher decile based on the number of employed analysts (highest), no change or change within the same decile (middle), move down (low), and leave the profession (lowest). Deciles 1 and 10 are excluded from the regressions. The Full Sample is described in Appendix A. See Appendix B for variable descriptions. *** (**, *) Two-tail test indicates significantly different from 0 at the 1% (5%, 10%) level. ^{1} (^{2}, ^{3}) One-tail test indicates for each trait, *TopBank* coefficient estimate is significantly less than *BottomBank* coefficient estimate, at the 1% (5%, 10%) level. Year and employer fixed effects are used in each regression and standard errors are adjusted for clustering along two dimensions; analyst and main followed industry, following Thompson (2011).

Table 8
Probit regressions with three dependent variables for type of analyst job switching, *Up*, *Down*, and *Depart*.

Panel A: Analysts Optimism						
Analyst report	Earnings forecasts			Stock recommendations		
Analyst job switch	*Up*	*Down*	*Depart*	*Up*	*Down*	*Depart*
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-1.23^{***}	-0.43^{***}	-0.45^{*}			
Accuracy	0.02	-0.22^{***}	-1.94^{***}			
Experience	-0.01^{***}	-0.03	-0.03^{***}			
Optimism x TopBank	$-0.22^{**,3}$	0.12^{**}	$1.15^{***,2}$			
Optimism x BottomBank	0.02	0.18^{***}	0.98^{***}			
N	24,688	25,960	26,599			
Panel B: Analysts Boldness						
Intercept	-1.17^{***}	-0.47^{***}	-1.41^{***}			
Accuracy	-0.01	-0.13^{*}	-1.03^{***}			
Experience	-0.01^{***}	-0.03	-0.03^{***}			
Boldness x TopBank	$-0.16^{**,2}$	$0.20^{**,3}$	$1.89^{***,1}$			
Boldness x BottomBank	-0.05	0.12	1.65^{***}			
N	24,688	25,960	26,599			
Panel C: Analysts ReportPiggybacking						
Intercept	-1.23^{***}	-0.39^{**}	-0.26	-1.25^{***}	-0.39^{**}	-0.19
Accuracy	0.01	-0.19^{**}	-1.78^{***}	0.03	-0.21^{***}	-1.61^{***}
Experience	-0.01^{***}	-0.03	-0.03^{***}	-0.01^{***}	-0.04	-0.02^{***}
ReportPiggy x TopBank	$-0.23^{**,2}$	-0.01	$0.49^{***,1}$	$-0.21^{**,3}$	$0.18^{**,3}$	$0.32^{***,1}$
ReportPiggy x BottomBank	0.03	0.02	0.35^{***}	0.10	0.07	0.12^{*}
N	24,688	25,960	26,599	22,726	23,929	24,471
Panel D: Analysts NewsPiggybacking						
Intercept	-1.22^{***}	-0.52^{***}	-0.28	-1.22^{***}	-0.43^{***}	-0.32
Accuracy	0.01	-0.19^{***}	-1.78^{***}	0.03	-0.22^{***}	-1.61^{***}
Experience	-0.01^{***}	-0.04	-0.03^{***}	-0.01^{***}	-0.04	-0.02^{***}
NewsPiggy x TopBank	$-0.26^{**,2}$	0.18^{**}	$0.62^{***,1}$	$-0.21^{**,2}$	$0.21^{**,2}$	$0.44^{***,1}$
NewsPiggy x BottomBank	-0.01	0.24^{***}	0.36^{***}	-0.04	0.09	0.27^{***}
N	24,688	25,960	26,599	22,726	23,929	24,471

The dependent variables are dummy variables for moving up to an employer in a higher decile, *Up*, moving down, *Down*, and one for departing the profession, *Depart*. The Full Sample is described in Appendix A. See Appendix B for variable descriptions. *** (**, *) Two-tail test indicates significantly different from 0 at the 1% (5%, 10%) level. ^{1} (^{2}, ^{3}) One-tail test indicates for each trait, *TopBank* coefficient estimate is significantly less than *BottomBank* coefficient estimate, at the 1% (5%, 10%) level. Year and employer fixed effects are used in each regression and standard errors are adjusted for clustering along two dimensions; analyst and main followed industry, following Thompson (2011).

Table 9
Probit regressions that include one bias and one shirking measure.

Panel A. Optimism and shirking trait

Shirking trait	*ReportPiggybacking*		*NewsPiggybacking*	
Variable	(1)	(2)	(3)	(4)
Intercept	-2.61***	-2.63***	-2.53***	-2.56***
Intercept2	0.47**	0.45**	0.56***	0.53***
Accuracy	1.30***	1.29***	1.30***	1.29***
Experience	0.02***	0.02***	0.02***	0.02***
Optimism	-0.74***		-0.76***	
Optimism x TopBank		-0.81***,3		-0.77***
Optimism x BottomBank		-0.70***		-0.72***
Shirking Trait	-0.16***		-0.37***	
Shirking Trait x TopBank		-0.21***,2		-0.50***,1
Shirking Trait x BottomBank		-0.06		-0.31***
N	24,049	24,049	24,049	24,049
Panel B. Boldness and shirking trait				
Intercept	-1.89***	-1.92***	-1.86***	-1.89***
Intercept2	1.22***	1.20***	1.25***	1.22***
Accuracy	0.70***	0.70***	0.71***	0.70***
Experience	0.02***	0.02***	0.02***	0.02***
Boldness	-1.19***		-1.19***	
Boldness x TopBank		-1.38***,1		-1.30***,2
Boldness x BottomBank		-1.16***		-1.16***
Shirking Trait	-0.27***		-0.29***	
Shirking Trait x TopBank		-0.34***,3		-0.40***,2
Shirking Trait x BottomBank		-0.23***		-0.26***
N	24,049	24,049	24,049	24,049

The dependent variable has three levels: move up to an employer in a higher decile based on the number of employed analysts (highest), no change or change within the same decile (middle), and move down or leave the profession (lowest). Deciles 1 and 10 are excluded from the regressions. The Full Sample is described in Appendix A. See Appendix B for variable descriptions. *** (**, *) Two-tail test indicates significantly different from 0 at the 1% (5%, 10%) level. Year and employer fixed effects are used in each regression and standard errors are adjusted for clustering along two dimensions; analyst and main followed industry, following Thompson (2011).

Table 10
Analyst chance of winning the *II Award.*

Years of experience	Chance of winning, survivorship adjusted (1)	Chance of winning, unadjusted (2)	Chance of surviving (3)
Panel A. An II Award at Top 10 bank			
3	1.40%	2.25%	62.05%
5	2.02%	4.85%	41.63%
10	1.47%	8.87%	16.56%
15	0.74%	10.39%	7.12%
Panel B. An II Award at Top 11-25 bank			
3	1.23%	2.06%	59.52%
5	1.16%	2.95%	39.34%
10	0.74%	4.11%	17.96%
15	0.35%	4.76%	7.32%
Panel C. An II Award at a BottomBank			
3	0.27%	0.50%	53.78%
5	0.25%	0.73%	34.15%
10	0.17%	1.19%	13.87%
15	0.07%	1.24%	5.44%

Panels A thru C report chances of winning an initial *II Award*, by the end of year of experience, survivorship adjusted and unadjusted, for three measures of bank reputation, for the Full Sample. The Full Sample is described in Appendix A. See Appendix B for variable descriptions.