Are Stars' Opinions Worth More? The Relation Between Analyst Reputation and Recommendation Values

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Journal of Financial Services Research

ISSN 0920-8550
Volume 46
Number 3

J Financ Serv Res (2014) 46:235-269
DOI 10.1007/s10693-013-0178-y


JFSR

Journal of Financial Services Research

CONTENTS

Bank Competition and Loan Quality
F. Gomez · J. Ponce **215**

Are Stars' Opinions Worth More? The Relation Between Analyst Reputation and Recommendation Values
L.H. Fang · A. Yasuda **235**

Bank Productivity Change and Off-Balance-Sheet Activities Across Different Levels of Economic Development
A. Lozano-Vivas · F. Pasiouras **271**

Relationship Lending and Credit Quality
F. Fiordelisi · S. Monferrà · G. Sampagnaro **295**

Vol. 46, No. 3, December 2014

Springer

ISSN 0920-8550

Springer

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Are Stars' Opinions Worth More? The Relation Between Analyst Reputation and Recommendation Values

Lily H. Fang · Ayako Yasuda

Received: 16 July 2012 / Revised: 16 August 2013 / Accepted: 22 August 2013 /
Published online: 26 October 2013

Abstract Using 1994–2009 data, we find that All-American (AA) analysts' buy and sell portfolio alphas significantly exceed those of non-AAs by up to 0.6 % per month after risk-adjustments for investors with advance access to analyst recommendations. For investors without such access, top-rank AAs still earn significantly higher (by 0.3 %) monthly alphas in buy recommendations than others. AAs' superior performance exists *before* (as well as after) they are elected, is not explained by market overreactions to stars, and is not significantly eroded after Reg-FD. Election to top-AA ranks *predicts* future performance in buy recommendations above and beyond other previously observable analyst characteristics. Institutional investors actively evaluate analysts and update the AA roster accordingly. Collectively, these results suggest that skill differences among analysts exist and AA election reflects institutional investors' ability to evaluate and benefit from elected analysts' superior skills. Other investors' opportunity to profit from the stars' opinions exists, but is limited due to their timing disadvantage.

Keywords Analyst reputation · Star status · Stock recommendations · Institutional investors · Performance evaluation

We thank Yakov Amihud, Brad Barber, Mark Chen, David Musto (the editor), Edwin Elton, Steve Figlewski, Gary Gorton, Martin Gruber, Pierre Hillion, Chris James, Kose John, Xi Li, Alexander Ljungqvist, Chris Malloy, Felicia Marston, Andrew Metrick, Jay Ritter, Michael Roberts, Michael Schill, Rob Stambaugh, Laura Starks, James Vickery, Bill Wilhelm, Kent Womack, Jeff Wurgler, an anonymous referee, and the seminar and conference participants at Florida, INSEAD, NYU, Virginia, Wharton, the 1st Saw Centre for Financial Studies Conference on Quantitative Finance, the AFA meetings (Boston), the EFA meetings (Zurich), and 9th Conference of the Swiss Society for Financial Market Research (Zurich) for helpful discussions, and I/B/E/S for making their data available for academic use. Financial support from the Wharton Rodney L. White Center for Financial Research, the INSEAD R&D Committee, and the INSEAD/Wharton Alliance is gratefully appreciated. Shichang Cao, Ben Lin, and Dong Yi provided excellent research assistance. All errors and omissions are our own.

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JEL Classification G1 · G2

1 Introduction

Stock analysts play a key role in collecting, interpreting, and disseminating company information to investors. Issuing "buy" and "sell" recommendations is an important part of an analyst's job and one of the most visible ways for the analyst to express his/her opinions on the securities covered. Economic theory tells us that in a market of opinion provision such as the analysts', since the product is intangible and *ex ante* hard to evaluate, reputation of the analysts—which we measure by the prestigious All-American (AA) title—should play an important role in signaling quality,[1] thus predicting a positive relation between star status and recommendation values. But in reality the validity of this prediction is less than warranted, because institutional investors elect AA analysts and their election criteria are not limited to the analysts' published research. In fact, earnings forecast accuracy and stock picking are typically listed near the bottom of a dozen or so criteria that institutional investors say they value in star analysts. In contrast, "responsiveness" is ranked highly, suggesting that institutional investors value information that is passed along in private communications rather than research reports.[2] Is the star status that emerges from such a process still positively related to (published) research quality? This concern is particularly relevant for recommendations as compared with forecasts: While forecasts are precise numbers, the accuracy of which can be quantified, recommendations are "opinions", so analysts may have incentives to issue favorable ones to "curry favor" (Bradley et al. (2008)) with company management.

Much prior research documents a positive relation between the AA status and *earnings forecast* quality. But evidence on the relation between the AA status and recommendation values is mixed; researchers disagree whether star status is positively related to analyst performance when it is measured using their buy/sell calls (a detailed literature review is in Section 2). Furthermore, the source of outperformance by star analysts, if any, is not well understood. We contribute to the literature by (i) using a comprehensive dataset between 1994 and 2009 and well-established portfolio performance metrics to examine the empirical relation between the AA status and recommendation values, and (ii) to posit and distinguish among three hypotheses pertaining to the source of AA outperformance. First, the ***irrelevant AA hypothesis*** maintains that factors determining AA election outcomes are orthogonal to analyst performance, and there is no relation between AA status and the investment value of their recommendations. Second, in the ***skilled AA hypothesis***, some analysts are more skilled than others (or acquire greater skill over time), and the AA status captures this ability difference. In other words, institutional investors' star election process identifies skill. Third, in the ***lucky AA hypothesis***, analysts are not skilled but simply lucky when they are first elected to star status —i.e., the recommendations they made pre-election happen to be right—but once they achieve AA status, success begets further success. We consider two specific channels. It may be that AAs are lucky and influential. In this case, once analysts become stars, they are perceived to have greater skill, and the market reacts more strongly to their recommendations (we call this variant the ***lucky-and-influential AA hypothesis***).

[1] Classic papers on the role of reputation in alleviating asymmetric information in financial markets include, for example, Diamond (1989) and Benabou and Laroque (1992).

[2] See October issues of the *Institutional Investor* magazine for various years, which announce AA election results and discuss the election criteria.

Alternatively, AAs may be lucky and well connected. In this case, once the lucky analysts are elected AAs, they gain superior access to the management of the firms they cover, which improves the quality of their research (we call this variant the ***lucky-and-connected AA hypothesis***).

Using data from 1994–2009, we compare the performances (alphas) of dynamic portfolios based on AAs' and non-AAs' buy and sell recommendations, both before and after elections, and also over different investment horizons. The pre- and post-election comparison informs us whether the performance difference is more likely due to skill (which would persist both before and after analysts' election to star status) or other factors such as luck (which would not persist). Investigating different horizons allows us to disentangle whether the performance difference stems from influence (which would be temporary and reversed) or information (which could come from either skill or connection, and would not be reversed). We further exploit Regulation Fair Disclosure (Reg-FD) as a natural experiment.[3] Passed in 2000, Reg-FD prohibited companies from making selective disclosures of material information to certain parties—notably research analysts. Thus, if AAs' advantage primarily comes from superior connection rather than skill (the ***lucky-and-connected AA hypothesis***), we expect the performance differential between stars and non-stars to diminish post-Reg-FD. Finally, there is variation across investors in their access to analysts' views. Institutional investors that have client relationships with the analysts frequently receive pre-release updates from analysts (Irvine et al. (2007), Juergens and Lindsey (2009))[4]; in contrast, most retail investors and investors without client relationships with the analysts are unlikely to have advance access to analyst recommendations. Importantly, the former (large institutional investors who are most likely to have advance access) are the dominant voters for the AA list.[5] Since the investment value of a recommendation clearly depends on when the information is received, it follows that the perceived performance of recommendations made by stars relative to other analysts might be measurably different depending on the investors' access to analyst information. We also shed light on this comparison.

We find a significantly positive relation between the AA status and performance in stock recommendations, and this performance differential is most consistent with the ***skilled AA hypothesis***. Specifically, our results can be summarized as follows. First, for investors with private, advance access to analyst recommendations (e.g., those on the analysts' client lists), risk-adjusted returns from AAs' recommendations exceed those from non-AAs' recommendations by about 0.6 % on a monthly basis. This holds for both buys and sells, and the magnitude is robust to a number of standard risk adjustments. For investors without such access, the opportunity to make excess profits from trading on stars' recommendations exists, but is more limited. Not only is the magnitude of gains smaller at 0.3 % per month, but also the outperformance is only found in buy recommendations made by top-ranked AAs (the minority of AAs that gain the top two awards in each sector

[3] Cohen et al. (2010) also use Reg-FD as a natural experiment in their study of the value of analysts' social network.

[4] Trading ahead of research reports is governed by Nasdaq Rule 2110–4 (http://www.sec.gov/pdf/nasd1/2000ser.pdf), which prohibits trading for a broker firm's own account in anticipation of a research report, but does not prohibit selective disclosure to clients. See Juergens and Lindsey (2009) for a detailed discussion of the rule and its interpretation.

[5] For example, the 2009 AA ranking was based on polls from more than 890 buy-side firms, including 87 of the 100 biggest U.S. equity managers (Kramer 2009). The 2001 AA ranking was sent to, among others, the II300, the magazine's ranking of the largest institutions in the U.S.. The *II* magazine weights various respondents based on the size of the voting institution (Dini 2001).

category each year). But overall there is a clear positive reputation-performance relation, refuting the ***irrelevant AA hypothesis***.

Second, we find very similar qualitative and quantitative differences in AAs' and non-AAs' performance both *before* and *after* the AA election results are announced. On the one hand, the pre-election performance differential between AAs and non-AAs indicates that it is unlikely to be due to either analyst influence or connections—both of which would be bestowed on the analysts after they are elected. On the other hand, the persistence of the performance differentials post-election suggests that it is unlikely to be due to luck alone. Furthermore, the quantitatively nearly identical performance differential between stars and non-stars both pre- and post-election casts strong doubt on both versions of the unskilled-but-lucky hypothesis as it would be an unlikely event for the (post-election) superior performance (due to either influence or connection) to exactly match the (pre-election) superior performance due to luck. In addition, we find that the performance differential does not reverse over time, does not disappear after Reg-FD, and is not driven by AAs relying more heavily on concurrent earnings news than non-AAs.

Collectively these results suggest that neither influence nor connection alone can explain the performance differential between stars and non-stars; skill differences among analysts exist and at least partially explain star analysts' outperformance. We acknowledge that the hypotheses are not mutually exclusive—influence, connection, and skill may all be at play for some analysts and some periods—and thus do not claim that the *entire* performance differential derives from superior skill of AAs. Rather, our findings support the view that at least part of the AA outperformance comes from skill. Our results also indicate that institutional investors—who elect the AAs—are best positioned to profit from star analysts' views; the ability of other investors to "piggyback" on the AA status as a signal of analyst skill and make excess profits from these analysts' recommendations is limited. If evaluating analysts is costly, these results are consistent with the Grossman and Stiglitz (1980) notion of market efficiency: Benefit of information production accrues mostly to the investors who produce the information.

We provide additional evidence that institutional investors actively evaluate analysts. First, we examine whether the AA status predicts future analyst performance *above and beyond* other observable characteristics. Sorting analysts according to their ex-ante likelihood of being elected AAs based on observable characteristics, we find that even among analysts with similarly high likelihood of being elected, actual election to AA ranks (especially top ranks) *predicts* future performance in buy recommendations. Thus, the AA status contains information above and beyond observable characteristics and cannot be completely replicated by investors who only utilize analysts' other observable characteristics. Second, we analyze institutional investors' dynamic responses to changes in the analysts' labor market in the 2002–2003 period. During this period, a series of regulation changes had significant impacts on sell-side research. While Rule 2711 (which came into effect in 2002) put tremendous pressure on analysts to decrease (increase) proportions of buys (sells) among their recommendations, the Global Settlement of 2003 led to significant budget cuts and smaller compensation packages for top analysts.[6] We document that turnover rates among analysts were unusually high during this period; in particular, many

[6] In late 2002, NASD Rule 2711 came into effect which required brokerage firms to disclose the distribution of their buys, holds, and sells in all their research reports; In early 2003, the Global Settlement was reached between regulators and 12 large brokerage firms where combined $1.4 billion in fines were charged for publishing overly optimistic research. The median pay of sell-side analysts fell from $230,000 in 2001 to $155,000 in 2003, according to the CFA Institute (Schack 2004).

experienced AAs with good past performance departed from the analyst profession altogether.[7] In response, institutional investors reshuffled the remaining AA pool by promoting a number of new names and demoting some old stars. Consistent with the notion that institutional investors actively evaluate analysts and update the AA roster accordingly, we find that these promotions/demotions done by institutional investors were by and large rational and effective: The demoted ex-stars indeed lagged behind in performance *both before and after* their falls, and the promoted new stars showed strong performance both before and after their rises. Thus these reshuffling decisions helped mitigate the negative effect of the AA exodus from the profession on the performance of the AA pool.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 discusses our data. Section 4 presents our main results and Section 5 examines different hypotheses. Section 6 provides additional analyses. Section 7 concludes.

2 Literature

This paper focuses on the empirical relation between analysts' star status —a proxy for reputation[8]—and the investment value of their *recommendations* (instead of earnings forecasts) for two reasons. First, while much has been studied about analyst research, researchers do not agree whether star status is positively related to analyst performance in the case of stock recommendations.[9] Second, the source of star analysts' outperformance (to the extent it exists) is not well understood. Our contribution to the literature is (i) to use a long dataset and well-established performance metrics to shed light on the debate about whether stars outperform non-stars, and (ii) to examine whether the outperformance stems from superior skill or other sources (such as influence and/or connection).

Stickel (1995) is one of the first to explore factors influencing short-term price reactions to analyst recommendations. Using a small sample from 1988–1991, he finds the AA title to

[7] Anecdotally, these high-performing former AA analysts often accepted high-paying positions at hedge funds or moved to proprietary trading within brokerage firms. For example, Samuel Buttrick, who ranked first in the Airlines category for 9 years, moved from UBS's research department to its proprietary trading team in 2003 (Schack 2004).

[8] A number of papers examine other analyst characteristics that may be related to skill, but not the star status. Mikhail et al. (2004) and Li (2005) focus on analysts with superior past performance. Cooper et al. (2001) identify "lead analysts" by the timeliness of their forecasts. Bonner et al. (2007) use media coverage of analysts to proxy for analyst "celebrity". Both past performance and celebrity status may be correlated with, but are distinct from, star status. We report below that while measures of past performance are statistically significant in predicting star election, much of actual election outcome is unexplained by such variables. Bonner et al. (2007) report that their measure of celebrity is distinct from the AA status.

[9] Papers studying analyst forecasts (e.g., Stickel (1992), Cowen et al. (2006), Hong et al. (2000), Hong and Kubik (2003), Gleason and Lee (2003), Jackson (2005), and Fang and Yasuda (2009) among others) find a positive relation between analyst reputation and earnings forecast quality (measured by forecast accuracy and/or bias). But a positive reputation-performance relation in forecasts need not translate to a positive reputation-performance relation in recommendations. Forecasts are precise numbers whose accuracy can be easily observed by investors, whereas recommendations are softer targets. An analyst may have a strong incentive to provide accurate forecasts in order to be seen as "smart", but may use recommendations opportunistically (e.g., by showing an optimistic bias) to "curry favor" with company management, which is key for information access. Empirical evidence on the consistency between forecasts and recommendations is mixed. Malmendier and Shanthikumar (2007) document differences between forecasts and recommendations; Hall and Tacon (2010) find that analysts with accurate past forecasts do not make more profitable recommendations in the future. In contrast, Loh and Mian (2006) and Ertimur et al. (2007) find that analysts who make more accurate forecasts also make more profitable recommendations. Also see Lin and McNichols (1998), Clarke et al. (2007), Brown and Huang (2010), and Kecskes et al. (2010).

be positively related to the short-term price reactions along with a number of other factors. Using data from 1993–2005, Emery and Li (2009) find that pre-election recommendation performance has a significantly positive impact on AA analysts' probability of being re-elected as well as moving to a higher rank, but there is no performance persistence post election, leading them to conclude that analyst rankings are largely "popularity contests". Using data from 1991–2000, Leone and Wu (2007) find a positive relation between the AA title and short-term recommendation performance pre-election, but unlike Emery and Li (2009), they find this performance to persist post-election and conclude that stars' superior performance is due to superior ability rather than luck.

While the literature is informative, our paper sheds new light on questions not examined by existing studies, namely, do star analysts make more profitable recommendations than non-stars that are not merely due to initial announcement effects, and do they continue to make profitable recommendations after Reg-FD shut down privileged access to company management? Stickel (1995) and Leone and Wu (2007) use data before Reg-FD and a number of other important regulation changes; both papers also use short-run price reactions as performance metrics as opposed to longer-term returns. We use data from 1993–2009, which allows us to examine periods both before and after a number of regulation changes that took place between 2000 and 2003. Emery and Li (2009) calculate the information ratio as their key performance metric, which is the *t*-statistic for the intercept of a regression of daily analyst recommendation returns on an index for the analyst's industry within a calendar year. While this is a measure of analyst research quality, it is not a direct measure of performance; it also punishes recommendations with more volatile idiosyncratic returns, even if the mean is higher. Methodologically, we sort analysts according to their AA status and form calendar-time buy and sell portfolios for each group. We then calculate a time series of daily returns and estimate standard risk-adjusted alphas for each portfolio. This approach produces a metric that is based on the well-established performance measurement literature: the alphas we compute are analogous to performance metrics used to evaluated fund managers. Apart from these methodological differences in addressing the question of *whether* star analysts make more valuable recommendations, we contribute to this literature by proposing and testing different hypotheses about *why* star analysts may have superior performance. While Leone and Wu (2007) also examine this question, our use of portfolio alphas based on long-term returns as opposed to initial announcement effects helps us isolate the ***skilled AA hypothesis*** from the ***lucky-and-influential AA hypothesis***; our use of data post-2000 further enables us to distinguish between the ***skilled AA hypothesis*** and the ***lucky-and-connected AA hypothesis***.

More recently, Loh and Stulz (2011) use data from 1993–2006 and find that only 12 % of all recommendations are influential (in the sense that they elicit statistically significant price response or increased trading in the right direction) and that these recommendations are more likely to be made by star analysts. This is consistent with our conclusion that there is a positive relation between reputation and recommendation profitability, but our paper differs in two ways. First, Loh and Stulz (2011) do not examine whether the influence differential is due to skill or other factors such as market overreaction or access to management, whereas one of our main contributions is to distinguish among these alternatives. Second, we focus on identifying *analysts* whose recommendations earn significantly higher risk-adjusted returns than others, whereas Loh and Stulz (2011) identify *individual stock recommendations* that move the market.

A number of papers document a significant impact of Reg-FD on analyst research. Bailey et al. (2003), Mohanram and Sunder (2006), and Gomes et al. (2007) suggest that Reg-FD made forecasting more difficult and put greater demands on analysts to generate idiosyncratic information. Cohen et al. (2010) document that analysts connected with company boards (through school ties) generate more profitable recommendations, but the effect disappears after Reg-FD, indicating that the regulation removed a source of well-connected analysts' informational advantage. Gintschel and Markov (2004) and Mohanram and Sunder (2006) document that the information advantage of analysts working at large brokerages dissipated post Reg-FD. In contrast, we find that star analysts' superior performance did not disappear post Reg-FD, suggesting that AAs (or at least some of the AAs) differ from non-stars beyond having better connections.

A few papers examine shifts in analysts' labor market around regulatory changes. Bagnoli et al. (2008) argue that AAs elected after Reg-FD built a competitive advantage that depends less on privileged access to the management. Guan et al. (2010) document that AAs who leave the profession after 2002 are more likely to move to the buy side than before, and that departing AAs performed better than other analysts covering the same firms. We examine changes in the AA pool following Rule 2711 and the Global Settlement (which we refer to collectively as the conflicts-of-interest reforms). We document unusually high turnover among experienced, outperforming AAs after the conflicts-of-interest reforms, many of whom left sell-side research. These departing AAs performed better than not only non-AAs but also the remaining AAs. We further show that as a response to these changes, institutional investors rationally reshuffled the AA pool and mitigated the effects of these labor-market movements on the performance of the AA pool. Results in both Bagnoli et al. (2008) and this paper suggest that the AA election process is able to respond to changes in the industry and continue to identify analyst talent.

The related question of whether analysts' stock recommendations have investment value *in general* has been extensively studied. The conclusion from a large volume of work (e.g., Elton et al. (1986), Womack (1996), Barber et al. (2001), Bradley et al. (2003), Irvine (2003), Jegadeesh et al. (2004), Boni and Womack (2006), and Jegadeesh and Kim (2006)) is that stock recommendations contain information; investors can earn positive risk-adjusted returns (gross of trading costs) by following stock recommendations promptly.[10] However, the recent works by Altinkiliç and Hansen (2009) and Altinkiliç et al. (2010) challenge this long-standing view and argue that *on average*, analyst forecasts and recommendation revisions piggy-back on public information and do not provide new information once the impact of other firm-specific news is removed. While our work focuses on the cross-sectional difference in recommendation performance rather than the average case, we need to be concerned if, for example, AAs' recommendations piggy back more on news events than those of non-AAs. To address this concern, we re-examine our results after removing recommendations made within a 3-day window of quarterly earnings announcement dates—the most important type of public news identified by Altinkiliç and Hansen (2009)—and find the performance differential between the AAs and non-AAs unchanged.

3 Data and descriptive statistics

We obtain recommendation data from the I/B/E/S Detailed History file. Our main dataset consists of 392,711 unique recommendations from October 1993 to December 2009.[11] Stock returns are collected from the CRSP daily stock file and merged with the I/B/E/S data.

[10] Balakrishnan et al. (2011) go further and provide evidence that analyst recommendations (rather than forecasts) play a role in bubbles and post-news price drift by influencing traders' higher-order beliefs (beliefs about other traders' beliefs about a stock's valuation).

[11] Ljungqvist et al. (2009) report that records in the I/B/E/S recommendations data were altered for downloads between 2002 and 2004. They also report that I/B/E/S corrected these problems after Feb 12, 2007. Our data sample is downloaded on March 8, 2010 and is thus free from potential biases documented by Ljungqvist et al. (2009).

As a metric for analysts' star status, we use the AA title awarded by the influential *Institutional Investor* magazine.[12] Information on the AAs is collected manually from the magazine for each year and matched by name with the I/B/E/S dataset through its translation file; we manually check and resolve inconsistencies in analyst names over time (e.g., due to changes in marital status). An analyst's AA status lasts from October of the year of election to September of the following year.

The AA title is awarded to top analysts in each of sixty or so industry sectors and has four rankings: first place, second place, third place, and runner-up. First and second place AAs account for about one-third of the AA pool, since each of these awards is given to one analyst per industry each year, whereas several analysts often share the runner-up awards. In addition to comparing the performance of AAs to non-AAs, we also differentiate among the ranks of AAs, classifying first and second place winners as top-rank AAs, and third-place and runners-up as bottom-rank AAs.

Table 1 presents summary statistics of the merged sample. The number of firms receiving analyst recommendations peaks in the late 1990's and declines sharply around 1999–2000. This drop in coverage is related to Reg-FD and other regulations following analyst scandals during the tech bubble (Fang and Yasuda (2009)). AAs comprise only 8 % of all analysts but 12 % of all recommendations (Panel A), indicating that, per individual, AAs make more recommendations than non-AAs. In Panel B, We report that AA analysts (both top-rank and bottom-rank AAs) cover significantly more stocks per analyst (about 8) than non-AAs (about 5), while there is generally no significant difference in the number of stocks covered per analyst between top-rank AAs and bottom-rank AAs.

Table 2 provides information on the AA election process. Panel A tabulates the distribution of AA tenure (in years) among the 1,229 unique AAs in our sample. The distribution is skewed: 48 % of analysts ever elected as an AA stay on the list for 3 years or fewer, 20 % have tenures of 4 or 5 years, and 10 % have tenures of 10 years or more. Separately (unreported), we find that while the average tenure is 5.9 years, it is 8.1 years among those who ever attain top ranks (first or second place) and 3.8 years among the rest, the difference being highly significant. When an analyst is elected for the first time, he/she typically debuts as a bottom-rank AA. These patterns suggest that, while most AAs get elected a couple of times (which can be due to luck), a minority gets elected repeatedly, and that minority is more likely to attain the top ranks, which are associated with the largest financial rewards.[13]

Panel B shows the annual transition probabilities among different analyst rankings conditional on analysts remaining in the sample. AA election is highly persistent: Around two-thirds of top- and bottom-rank AAs remain as top- and bottom-rank AAs, respectively,

[12] Each spring, typically in April or May, *Institutional Investor* conducts a large survey among buy-side managers, asking them to evaluate sell-side analysts along the following four dimensions: stock picking, earnings forecasts, written reports, and overall service. The survey results lead to the annual election of the AA analysts, which is published in the magazine's October issues.

[13] According to *Institutional Investor*'s 2007 analyst compensation survey (Oct 2007), the average cash compensation of senior analysts in 2006 was more than half a million dollars, whereas AA analysts commanded more than \$1.4 million. Sessa (1999) and Hong et al. (2000) also discuss financial and professional rewards associated with AA titles. Banks reward AA analysts because they bring in business flows. See, for example, Krigman et al. (2001), Dunbar (2000), Ljungqvist et al. (2006), Clarke et al. (2007), Cliff and Denis (2004), and Liu and Ritter (2010).

Table 1 Descriptive statistics. This table presents summary statistics of the recommendation sample. Panel A reports the numbers of firms, analysts, and recommendations made by different types of analysts; Panel B reports the average number of stocks covered per analyst for different types of analysts. Figures in this table are reported on an election-year basis, which runs from October of a given year (when the All-American winners for that year are announced in the *Institutional Investor* magazine) to September of the next year. An AA is an analyst whose name appears in the *Institutional Investor* as an "All American" title winner. Recommendations made by AAs from the October of the winning year to the September of the next year inclusive are coded as "AA" recommendations. A top-rank AA refers to an analyst winning the first-team or the second-team title in his respective sector. A bottom-rank AA is an analyst who wins the third-team or runner-up title in his sector. The number of bottom-rank AAs decreased in 2009 because no runner-ups were announced in that year

Panel A: Numbers of firms, analysts, and recommendations

Election year	Firms	Analysts	non-AAs (%)	AAs (%)	Top-rank AAs (%)	Bottom-rank AAs (%)	Recommendations	Non-AAs (%)	AAs (%)	Top-rank AAs (%)	Bottom-rank AAs (%)
1993	4,530	1,962	85 %	15 %	4 %	11 %	28,924	77 %	23 %	6 %	18 %
1994	4,443	2,196	86 %	14 %	3 %	10 %	19,727	81 %	19 %	5 %	14 %
1995	4,881	2,482	91 %	9 %	3 %	6 %	19,818	88 %	12 %	5 %	7 %
1996	5,081	2,810	92 %	8 %	3 %	5 %	19,561	89 %	11 %	5 %	6 %
1997	5,391	3,277	92 %	8 %	3 %	5 %	22,465	88 %	12 %	5 %	7 %
1998	5,039	3,603	92 %	8 %	3 %	5 %	23,302	88 %	12 %	4 %	8 %
1999	4,341	3,394	91 %	9 %	3 %	6 %	17,575	88 %	12 %	5 %	7 %
2000	3,489	3,175	92 %	8 %	3 %	5 %	16,136	87 %	13 %	6 %	8 %
2001	3,749	3,464	92 %	8 %	3 %	5 %	23,363	85 %	15 %	6 %	9 %
2002	3,628	3,268	93 %	7 %	3 %	5 %	20,160	90 %	10 %	4 %	6 %
2003	3,786	3,230	93 %	7 %	3 %	5 %	19,722	92 %	8 %	3 %	5 %
2004	3,967	3,420	93 %	7 %	2 %	4 %	19,564	91 %	9 %	3 %	6 %
2005	4,006	3,395	93 %	7 %	2 %	5 %	19,310	92 %	8 %	3 %	5 %
2006	4,062	3,414	94 %	6 %	2 %	4 %	20,603	91 %	9 %	3 %	6 %
2007	3,848	3,355	93 %	7 %	3 %	4 %	21,861	90 %	10 %	5 %	6 %
2008	3,401	3,120	93 %	7 %	3 %	4 %	19,874	90 %	10 %	5 %	5 %
2009*	2,126	1,910	94 %	6 %	4 %	2 %	4,799	93 %	7 %	5 %	2 %
Average**	4,228	3,098	92 %	8 %	3 %	5 %	20,748	88 %	12 %	4 %	8 %

Table 1 (continued)

Panel B: Number of stocks covered per analyst

Election year	AAs	Non-AAs	*t*-stat for equality	Top-rank AAs	Bottom-rank AAs	*t*-stat for equality
1993	18.8	10.8	10.79	18.8	18.8	0.03
1994	9.6	6.7	7.66	10.5	9.3	1.28
1995	8.9	6.4	6.04	9.4	8.6	0.96
1996	8.6	5.7	6.08	10.0	7.7	2.21
1997	8.7	5.5	7.34	9.0	8.4	0.70
1998	7.8	5.2	7.46	8.1	7.7	0.56
1999	6.3	4.4	6.50	7.1	5.9	1.68
2000	6.6	4.1	8.06	7.4	6.1	1.94
2001	10.8	5.1	12.05	11.5	10.4	1.11
2002	7.3	4.8	6.09	8.1	6.9	1.39
2003	5.9	4.9	3.03	6.2	5.8	0.65
2004	6.2	4.6	5.71	6.1	6.3	-0.38
2005	5.7	4.6	3.89	6.1	5.5	0.95
2006	6.9	4.8	5.01	6.6	7.1	-0.51
2007	8.4	4.9	8.11	8.8	8.1	0.86
2008	7.0	5.0	5.46	7.5	6.6	1.16
2009*	2.7	2.4	1.21	2.9	2.3	1.49
Average**	8.3	5.1	27.9	8.4	8.3	0.55

*: Our sample ends in Dec 2009 so it only covers the first three months of election year 2009

**: This average excludes election year 2009

Table 2 Statistics on AA election. This table reports summary statistics on the AA election. Panels A and B are based on *Institutional Investor* magazine's annual AA list from 1993–2009. Panel C reports Fama-McBeth regression results of probit analysis of AA election and uses data from the I/B/E/S Detailed History forecast file from 1983–2009. *ERROR* is the average forecast error (scaled by book-value per share) made by an analyst in the previous year. *BIAS* is the average forecast bias (signed forecast error, also scaled by book-value per share) made by an analyst in the previous year. *BOLDNESS* is the average deviation of an analyst's forecasts from consensus forecasts of the same stock in the previous year. *FREQUENCY* is the average number of times an analyst updates a forecast in the previous year. *COVERAG*E is the number of stocks for which an analyst provides fiscal-year-end earnings forecasts in the previous year. *EXPERIENCE* is the number of years an analyst appears in the sample up to the previous year. *PRESTIGE* is the 1998 Carter-Manaster ranking of the bank that the analyst works for

Panel A: AA-tenure distribution

AA Tenure (years)	Freq.	Percent
1	256	20.8 %
2	205	16.7 %
3	134	10.9 %
4	143	11.6 %
5	99	8.1 %
6	86	7.0 %
7	65	5.3 %
8	60	4.9 %
9	58	4.7 %
10	38	3.1 %
11	29	2.4 %
12	23	1.9 %
13	15	1.2 %
14	7	0.6 %
15	5	0.4 %
16	2	0.2 %
17	4	0.3 %
Total	1,229	100.0 %

Panel B: Transition matrix

To:	Top-rank AA	Bottom-rank AA	Non-AA	Total
From:				
Top-rank AA	69.8 %	24.2 %	6.0 %	100.0 %
Bottom-rank AA	18.8 %	59.3 %	21.9 %	100.0 %
Non-AA	0.3 %	1.8 %	97.9 %	100.0 %

Panel C: Probit regressions of AA election

	Election to AA		Election to top-rank AA	
	Coef.	*t* -stat	Coef.	*t* -stat
ERROR	−1.66	−4.25 ***	−2.25	−4.70 ***
BIAS	0.47	1.24	0.94	2.02 ***
BOLDNESS	0.04	0.72	−0.08	−1.37
FREQUENCY	0.16	14.12 ***	0.11	14.87 ***
COVERAGE	0.33	9.49 ***	0.23	5.65 ***
EXPERIENCE	0.75	8.04 ***	0.58	11.01 ***
PRESTIGE	0.92	26.40 ***	0.73	18.23 ***
CONSTANT	−3.86	−33.97 ***	−3.87	−41.07 ***
Pseudo-R^2	24 %		18 %	

*, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % level, respectively

from year to year. Nearly 98 % of non-AAs in a given year remain non-AA in the following year, leaving just 2 % to enter the AA ranks.

Panel C reports determinants of AA election using probit regression models. The results reveal that inaccurate past forecasts (*ERROR*) significantly reduce analysts' chances of being elected. Frequency of forecast updates (*FREQUENCY*), breadth of coverage (*COVERAGE*), experience (*EXPERIENCE*), and prestige of the brokerage where the analyst works (*PRESTIGE*) are rewarded in the election. These patterns suggest that the AA status is correlated with ex ante proxies of analyst quality. They are also consistent with claims made by the institutions (which elect the AAs) that the election is based on criteria such as "industry knowledge" and "communication". Our probit model explains over 20 % of the variation in AA election (18 % of the election to top ranks), comparable to other recent studies (e.g., Emery and Li (2009) and Leone and Wu (2007)).

4 Risk-adjusted portfolio return results for 1994–2009

4.1 Methodology

We investigate whether stars' opinions are worth more by dividing the recommendation sample into analyst groups—AAs, non-AAs, top-rank AAs, and bottom-rank AAs—and constructing dynamic portfolios based on these recommendations and comparing the risk-adjusted returns (alphas) of the portfolios. For each group, we form distinct "buy" and "sell" portfolios to detect asymmetries between bullish and bearish recommendations. Specifically, we code I/B/E/S ratings 1 and 2 as "buys" and I/B/E/S ratings 3, 4, and 5 as "sells"[14] and place new buys and sells (excluding re-iterations) in the respective portfolios.[15]

Following the methodology in Barber et al. (2006, 2007), we create calendar-time portfolios that invest $1 in each new recommendation. For each recommendation n, let $X_{n,t}$ denote the cumulative total return of stock i_n from the recommendation date to a future date t; that is,

$$X_{n,t} = R_{i_n,recdat_n} R_{i_n,recdat_n+1} * \ldots * R_{i_n,t}, \tag{1}$$

[14] Banks have distinct systems for coding their analyst recommendations, but typically had five levels corresponding to strong buy, buy, hold, sell, and strong sell. Prior to 2002, I/B/E/S translates the different systems used by banks to a numeric coding system on a scale of 1–5, where 1 refers to the strongest positive recommendation and 5 to the strongest negative recommendation. Around 2002, many banks switched from a 5-grade system to a 3-grade system, corresponding to overweight, market-weight, and under-weight (Kadan et al. (2009)). I/B/E/S translates the three levels as 2, 3, and 4; thus our classification is still valid.

[15] This construction means that we focus on revisions between the buy/sell categories. We conduct robustness checks where we examine revisions between the finer recommendation levels and find quantitatively very similar results. We also examine re-iterations under both construction methods separately, and find that re-iterations generate much lower levels of alpha (although still statistically significant). Alpha differentials among analyst groups are generally not significant on re-iterations. These results (unreported and available upon request) confirm that new recommendations are more informative than re-iterations.

where $R_{i_n,t}$ is the total return of stock i_n on calendar date t. The (calendar) date-t return on portfolio p containing recommendations n=1,…, N_{pt} is:

$$R_{pt} = \frac{\sum_{n=1}^{N_{pt}} X_{n,t-1} R_{i_n,t}}{\sum_{n=1}^{N_{pt}} X_{n,t-1}}, \tag{2}$$

where N_{pt} is the number of recommendations held in portfolio p on date t. Note that $X_{n,t-1}$ is the cumulative value of \$1 invested in recommendation n from the recommendation date up to (the close of) date t-1. Thus, the denominator of (2) is the open value of portfolio p on date t. Equation (2) is the value-weighted return of portfolio p on date t using $X_{n,t-1}$ as the weight of recommendation n in the portfolio.

In our baseline analysis, each position is held for 30 days; we also examine different horizons in additional analysis.[16] For each portfolio, the above calculation yields a time-series of daily returns from 1/3/1994–12/31/2009. We then calculate the risk-adjusted returns using the CAPM, Fama-French 3-factor model, and the Carhart 4-factor model, as follows:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p \left(R_{m,t} - R_{f,t} \right) + \varepsilon_{p,t} \tag{3}$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p1} \left(R_{m,t} - R_{f,t} \right) + s_p SMB_t + h_p HML_t + \varepsilon_{p,t} \tag{4}$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p1} \left(R_{m,t} - R_{f,t} \right) + s_p SMB_t + h_p HML_t + m_p WML_t + \varepsilon_{p,t} \tag{5}$$

where $R_{p,t}$ is portfolio p's return on date t; $R_{m,t}$ and $R_{f,t}$ are the market return and risk-free rate on date t, and SMB_t, HML_t, and WML_t are the size, book-to-market, and momentum factor, respectively.[17]

Because our sample period spans the tech bubble in the late 1990s and its subsequent collapse, there are concerns that (i) tech stock returns drove the overall performances of analyst stock recommendations, and (ii) analysts' (passive) loading on the tech-sector return is not appropriately controlled for in the standard factor models in Eqs. (3)–(5). We address these concerns in two ways. First, we remove all tech and internet-related stocks and report in this draft the performance of analysts covering non-tech stocks.[18] Second, in addition to

[16] In unreported robustness check analyses, we use 3-day, 7-day, 14-day, and 60-day holding periods and find that our main results are qualitatively unchanged, though the *levels* of alphas are (not surprisingly) higher the shorter the holding periods.

[17] See Fama and French (1993), Carhart (1997). Factor returns are obtained from Kenneth French's website.

[18] We use the list provided in Loughran and Ritter (2004) to identify tech stocks. We reported the results using the whole sample (both tech and non-tech stocks) in a previous version of this paper; the results (unreported and available upon request) are qualitatively identical to those of non-tech stocks reported in this paper, as the majority of analysts cover non-tech stocks. As for tech-stock portfolios (also unreported but available upon request), the raw returns and alphas are on average much higher, especially in the pre-2000 years. We find that tech AA analysts strongly and significantly outperform tech non-AA analysts, and the results are robust to controlling for the tech sector return (the 5-factor model).

Table 3 Baseline portfolio results. This table reports the monthly alphas of 30-day holding period portfolios that buy stocks at the close of the day before the recommendation dates. The buy portfolios (Panel A) include recommendations rated "strong buy" and "buy"; the sell portfolios (Panel B) include recommendations rated "hold", "sell", and "strong sell". Daily portfolio returns are calculated for the 1994–2009 period and portfolio alphas are estimated based on this daily return series. Portfolios consist of all non-tech stocks (identified from Loughran and Ritter (2004)) for which analysts issue new or revised recommendations (reiterations are excluded). Top-rank AAs are All-American analysts with either the 1st- or 2nd-place titles; bottom-rank AAs are All-American analysts with either the 3rd-place or runner-up titles. Risk-adjusted returns are calculated using the four alternative models: CAPM, the Fama-French 3-factor model, the Carhart 4-factor model (FF + momentum), and the five-factor model, which consists of the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return

	AAs	non-AAs	AA vs. non-AA difference	Top-rank AAs	Top-rank AA vs. non-AA difference	Bottom-rank AAs	Bottom-rank AA vs. non-AA difference	Top-rank AA vs. bottom-rank AA difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Buy recommendations								
Market-adjusted alpha	2.89 %	2.31 %	0.58 %***	3.00 %	0.70 %***	2.85 %	0.54 %***	0.15 %
FF 3-factor alpha	2.74 %	2.17 %	0.56 %***	2.82 %	0.64 %***	2.73 %	0.55 %***	0.09 %
Carhart 4-factor alpha	2.81 %	2.23 %	0.58 %***	2.91 %	0.69 %***	2.78 %	0.55 %***	0.14 %
Five-factor alpha (tech-return adjusted)	2.81 %	2.23 %	0.58 %***	2.92 %	0.69 %***	2.78 %	0.55 %***	0.14 %
Panel B: Sell recommendations								
Market-adjusted alpha	−3.42 %	−2.89 %	−0.53 %***	−3.43 %	−0.54 %**	−3.40 %	−0.51 %**	−0.03 %
FF 3-factor alpha	−3.61 %	−3.09 %	−0.53 %***	−3.66 %	−0.57 %**	−3.56 %	−0.47 %**	−0.10 %
Carhart 4-factor alpha	−3.43 %	−2.87 %	−0.56 %***	−3.46 %	−0.59 %**	−3.38 %	−0.51 %**	−0.08 %
Five-factor alpha (tech-return adjusted)	−3.43 %	−2.87 %	−0.56 %***	−3.46 %	−0.59 %**	−3.38 %	−0.51 %**	−0.08 %

*, **, and *** indicate that the *differences* between the alphas of various analyst groups reported in columns (3), (5), (7), and (8) are significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively. *Levels* of alphas are significantly different from 0 at 1 % significance level for all analyst types and risk adjustment models used

the standard factor models, we employ a 5-factor model, which consists of the Carhart 4 factors and the tech-sector index return[19]:

$$R_{p,t}-R_{f,t} = \alpha_p + \beta_{p1}\left(R_{m,t}-R_{f,t}\right) + s_p SMB_t + h_p HML_t + m_p WML_t + t_p Tech_t + \varepsilon_{p,t}. \quad (6)$$

Even non-tech stocks may have passive exposures to tech-sector returns. Such exposures are controlled for in the alpha of the five-factor model.

4.2 Baseline portfolio results

Table 3 reports the baseline risk-adjusted returns based on analyst recommendations from 1/1/1994 to 12/31/2009. We use asterisks to indicate that the *differences* between the alphas of various analyst groups — e.g., the difference between AA and non-AA alphas as reported in column (3) — are significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively.

First, the *levels* of alphas are significantly different from zero at 1 % significance level for all analyst groups, and in both buys and sells. This is consistent with prior findings (Womack (1996), Barber et al. (2001)), but indicates the robustness of the result even through the recent crisis years of 2007–2009. More importantly, when we examine the differences between alphas of various analyst groups, we find that *both* top-rank AAs and bottom-rank AAs significantly outperform non-AAs. The alpha differentials are always highly statistically significant for both buys and sells, and economically large—in the range of 0.6 % (monthly) in absolute value for both buys and sells. This magnitude is remarkably robust to the benchmark risk-adjustment models used.[20] Thus, AAs' recommendations are significantly more informative than those of non-AAs, refuting the *irrelevant AA hypothesis*.

Two notes should be made regarding the interpretation Table 3. First, in light of Altinkiliç and Hansen (2009) and Altinkiliç et al. (2010), one relevant concern is the possibility that AA recommendations piggyback more on public news than non-AA recommendations and thus the estimated alpha differential reflects such news effect rather than the pure recommendation value effect. To address this concern, we re-estimate portfolio returns after removing recommendations made within a 3-day window around any quarterly-earnings report dates.[21] Results are reported in Panel A of Table 4. While every analyst groups' alphas become more muted (in the sense that buy alphas become less positive and sell alphas become less negative) when we remove recommendations that are concurrent with earnings announcements (results here compared to Table 3), AAs' alphas decline (in absolute values) by *smaller* amounts (about 10 bps drops for buys and 20 bps drops for sells) than do non-AAs' alphas (about 20 bps drops for buys and 30 bps drops for sells). As a result, the alpha differentials between AAs and non-AAs are slightly larger than before at 0.6–0.7 %. Thus, the results suggest that, if anything, AAs piggyback less on earnings announcements than non-AAs do, and certainly not more.

[19] The tech index return used is ArcaEx Tech 100 Index (^PSE).

[20] In unreported analyses, we confirm robustness of the baseline results. First, we compute alternative portfolio returns using daily Daniel et al. (1997) benchmark-adjusted returns. Qualitative results regarding performance differentials between AAs and non-AAs are unchanged. Second, we use firm characteristics to estimate portfolio-specific trading commissions based on the method in Keim and Madhavan (1997) and compare the net-of-commission alphas. While the alphas for all groups are substantially lower net of trading cost, the AA–non-AA alpha differentials are *wider* after trading-cost adjustments. This is because AAs tend to cover stocks that are *cheaper* to trade (i.e., larger and NYSE-listed), while annual turnovers are similar between AAs and non-AAs.

[21] Quarterly earnings announcement dates are obtained from Compustat. We find about 10 % of revisions in our sample are made within the 3-day window around the earnings announcement dates, similar to the 12 % reported by Loh and Stulz (2011).

Table 4 Robustness results. Panel A of this table reports monthly alphas based on 30-day holding period portfolios after removing recommendations that are made within a 3-day window around quarterly earnings announcement dates. Panel B reports monthly alphas based on 30-day holding period portfolios where the investment in each recommendation is made at the close of the recommendation date. Daily portfolio returns are calculated for the 1994–2009 period and portfolio alphas are estimated based on this daily return series. Portfolios consist of all non-tech stocks (identified from Loughran and Ritter (2004)) for which analysts issue new or revised recommendations (re-iterations are excluded). Top-rank AAs are All-American analysts with either the 1st- or 2nd-place titles; bottom-rank AAs are All-American analysts with either the 3rd-place or runner-up titles. Risk-adjusted returns are calculated using the four alternative models: CAPM, the Fama-French 3-factor model, the Carhart 4-factor model (FF + momentum), and the five-factor model, which consists of the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return

	AAs	non-AAs	AA vs. non-AA difference	Top-rank AAs	Top-rank AA vs. non-AA Difference	Bottom-rank AAs	Bottom-rank AA vs. non-AA Difference	Top-rank AA vs. Bottom-rank AA Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Removing recommendations concurrent with quarterly earnings announcements								
A1: Buy recommendations								
Market-adjusted alpha	2.78 %	2.14 %	0.65 %***	2.85 %	0.72 %***	2.78 %	0.64 %***	0.07 %
FF 3-factor alpha	2.62 %	2.00 %	0.62 %***	2.65 %	0.65 %***	2.65 %	0.65 %***	0.00 %
Carhart 4-factor alpha	2.70 %	2.05 %	0.64 %***	2.76 %	0.70 %***	2.70 %	0.65 %***	0.05 %
Five-factor alpha (tech-return adjusted)	2.70 %	2.05 %	0.65 %***	2.76 %	0.71 %***	2.70 %	0.65 %***	0.06 %
A2: Sell recommendations								
Market-adjusted alpha	−3.21 %	−2.60 %	−0.61 %***	−3.21 %	−0.62 %**	−3.20 %	−0.60 %***	−0.02 %
FF 3-factor alpha	−3.41 %	−2.80 %	−0.61 %***	−3.45 %	−0.65 %**	−3.36 %	−0.56 %**	−0.09 %
Carhart 4-factor alpha	−3.21 %	−2.58 %	−0.64 %***	−3.24 %	−0.66 %***	−3.18 %	−0.60 %***	−0.06 %
Five-factor alpha (tech-return adjusted)	−3.21 %	−2.58 %	−0.64 %***	−3.24 %	−0.67 %***	−3.17 %	−0.60 %***	−0.07 %
Panel B: Delaying the time of investment								
B1: Buy recommendations								
Market-adjusted alpha	1.33 %	1.17 %	0.17 %	1.50 %	0.33 %*	1.24 %	0.07 %	0.26 %
FF 3-factor Alpha	1.18 %	1.04 %	0.14 %	1.32 %	0.28 %	1.13 %	0.08 %	0.19 %
Carhart 4-factor alpha	1.25 %	1.09 %	0.16 %	1.42 %	0.33 %*	1.18 %	0.08 %	0.24 %
Five-factor alpha (tech-return adjusted)	1.26 %	1.09 %	0.17 %	1.43 %	0.33 %*	1.18 %	0.08 %	0.25 %
B2: Sell recommendations								
Market-adjusted alpha	−0.82 %	−0.73 %	−0.09 %	−0.65 %	0.08 %	−0.91 %	−0.18 %	0.26 %
FF 3-factor alpha	−1.02 %	−0.93 %	−0.09 %	−0.89 %	0.03 %	−1.07 %	−0.14 %	0.18 %
Carhart 4-factor alpha	−0.83 %	−0.71 %	−0.12 %	−0.70 %	0.01 %	−0.88 %	−0.18 %	0.18 %
Five-factor alpha (tech-return adjusted)	−0.82 %	−0.70 %	−0.12 %	−0.70 %	0.00 %	−0.88 %	−0.18 %	0.18 %

*, **, and *** indicate that the differences between the alphas of various analyst groups reported in columns (3), (5), (7), and (8) are significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively. *Levels* of alphas are significantly different from 0 at 1 % significance level for all analyst types and risk adjustment models used

Second, while the alpha differentials in Table 3 indicate that stars' recommendations are more informative than others, it does not represent realizable excess profits from trading on stars' recommendations for the average investor. In order to capture total returns around recommendations, results in Table 3 include the recommendation-date return. This approach is consistent with a large body of existing literature (see, for example, Loh and Stulz (2011), Womack (1996), and Green (2006), among others).[22] However, to realize these returns, the investor would need to place the trade ahead of the recommendation release. Large institutional investors—who are analysts' main constituencies and who vote for star analysts—frequently obtain analyst updates before recommendation release (Juergens and Lindsey (2009) and Irvine et al. (2007)). Thus, one interpretation of Table 3 is that the 0.6 % monthly alpha differential represents realizable excess profits from trading on star analysts' recommendations relative to other analysts' *for investors with advance access to analyst information*. For such investors, stars' opinions are worth significantly (0.6 % per month) more than those of non-stars.

A natural question is whether investors without advance access can "piggyback" on star status and obtain higher returns by following star analysts' recommendations compared to following non-stars'. Our portfolio approach allows us to estimate this. To mimic the trading strategy of an investor without advance access, we delay the investment in each stock by one day compared to the baseline. Results are reported in Panel B of Table 4. These results contrast interestingly with Table 3. First, the levels of alphas are significantly lower across the board, indicating the rapid incorporation of information in stock prices, consistent with prior research (e.g., Barber et al. (2001)). Second, while the conclusion that stars' opinions are worth more is robust, the scope for the investor without advance access to make excess profits from stars' recommendations is somewhat limited. The alpha differentials are only significant in the buy category, and the outperformance is only concentrated among top-rank AAs—the minority of stars who obtain the 1st or 2nd ranking in each industry. The magnitude of the excess profit is also lower at around 0.3 % per month. Since the top-rank designation is highly selective even among AAs, these results reinforce the notion that there is a positive reputation-performance relation in recommendations. Finally, if evaluating analyst performance is costly, the contrast between Table 3 and Panel B of Table 4 is consistent with the Grossman and Stiglitz (1980) notion of market efficiency: Benefits of information production primarily accrue to (institutional) investors who collect the information, as institutional investors (who elect AAs) are much better positioned to make excess profits from trading on star analysts' recommendations. We provide additional evidence on institutional investors' ability to evaluate analysts in Section 6.

5 Why do stars outperform?

Having established a positive relation between reputation and recommendation performance, in this section we test a number of hypotheses regarding the sources of star analysts' outperformance.[23]

[22] Altinkiliç and Hansen (2009) discuss the empirical approach in existing literature in detail. Table 1 of the paper summarizes approaches used in widely cited papers.

[23] For brevity, we report in this section only portfolio results that include recommendation-date returns and thus reflect potential profits to investors with advance access to analyst information. In an earlier draft of the paper, we also report all corresponding results that exclude recommendation-date returns. These results are available upon request.

5.1 Are AAs just lucky and influential?

Since the baseline results in Table 3 are based on recommendations made *after* AA election outcomes are announced, they are consistent with multiple explanations. They are consistent with star analysts having superior skill (***the skilled AA hypothesis***). But it is also possible that analysts are merely lucky when they are first elected as stars, but post-election, they continue to outperform others due to either stronger market influence (the ***lucky-and-influential AA hypothesis***), or better access to company management (the ***lucky-and-connected AA hypothesis***). In both cases, success begets success; stronger influence and better connections are advantages bestowed on the lucky analysts by their star status, which allows them to perpetuate their superior performance.

To isolate the ***skilled AA hypothesis*** from both variants of the lucky-AA hypothesis, we construct portfolios based on recommendations made by analysts in the 12-month period *prior* to the announcement of the AA election outcomes.[24] If AAs' superior performance stems from bigger market influence or better connections *alone*—both of which come from their star status—we should not observe the same magnitudes of performance differentials pre-election.

Table 5 reports the pre-election performance results and shows that even in the *pre-election* period, future AAs significantly outperform non-AAs: the AAs' buy alphas are significantly larger than those of non-AAs in all models (asterisks next to column (3) indicating statistical significance of the alpha differentials). The sub-group analysis reported in columns (4)–(7) indicates that the result is mainly due to strong performances by future top-rank AAs. Notably, the alphas obtained in the pre-election periods (reported here) are nearly identical in magnitudes to those in the post-election periods (Table 3). On the one hand, the post-election result suggests that AAs are not just lucky: While luck might generate superior performance pre-election, it would not persist post election. On the other hand, the pre-election result indicates that AAs are not merely more influential or better connected, since these factors would generate post-election results but not pre-election. Furthermore, the striking *quantitative* similarity between the pre- and post-election results casts strong doubt on both the ***lucky-and-influential AA hypothesis*** and the ***lucky-and-connected AA hypothesis*** as the sole sources of the AA outperformance, as it would be unlikely that the top-rank AAs' (post-election) superior performance due to incremental influence or connection matches exactly their (pre-election) excess performance due to luck.

Next, we examine if the performance differentials are reversed over time. This is a specific test on the ***lucky-and-influential AA hypothesis***, which posits that AAs' superior performance stems from market (over-) reaction to their star status. If this is the only source of AA outperformance, excess return will be reversed over time (e.g., Kecskes and Womack (2010)). Table 6 compares analyst performances over 11 months from the end of the initial

[24] Since AA election results are announced in October, we use as "pre-election" the 12-month period before this announcement, i.e., the 12-month period ending in September each year. We choose this cutoff period because, though voting by institutional investors takes place around April, would-be AAs cannot start eliciting greater market responses or gaining superior access to the management until their status as AAs becomes public, which does not take place until October. We also conducted additional unreported analysis where we used an alternative definition of the pre-election period as the 12-month period starting in April of the year *prior to* the election year and ending in March of the election year (7 months before the announcement of AA election results in October). Our qualitative results are robust to this alternative specification — i.e., future AAs significantly outperform non-AAs, and the result is mainly due to strong performances by future top-rank AAs.

30-day period up to the 1-year anniversary of the recommendation date.[25] We find no significant difference between AAs and non-AAs for any of the models. Thus there is no evidence of return reversal in the post 30-day period.[26]

Combining the results of Tables 5 and 6, we can rule out the ***lucky-and-influential AA hypothesis*** as the dominant source of AA outperformance. AAs exhibit similar outperformance relative to non-AAs both before and after their elections, and there is no evidence of return reversal. However, we cannot yet rule out the ***lucky-and-connected AA hypothesis***, which maintains that star status provides AAs better access to management. Unlike market (over-) reaction to status alone, better access to management is a real source of information advantage and can generate performance differentials that do not reverse. Therefore, the return-reversal test above does not rule it out (although the nearly identical magnitudes of both pre- and post-election performance differentials cast doubt on it). We examine this hypothesis in the next sub-section.

5.2 Is AAs' superior performance driven by better access to management?

To investigate whether AAs' superior performance is primarily due to special access to the management, we exploit Reg-FD as a natural experiment. Introduced in 2000, Reg-FD was aimed to make company information more equally accessible to all. It disallowed selective information disclosure by company management to certain parties (primarily analysts), and required that all material information be made available to all interested parties simultaneously through public disclosure. This would significantly erode star analysts' superior performance if much of their advantage comes from having privileged access to company information. In contrast, if AAs' better performance stems largely from their superior ability—for example, to interpret and/or collect publicly available information about the firms without relying on private access to the management—then this regulation would not affect it much.

We conduct two tests to distinguish between the ***skilled AA hypothesis*** and the ***lucky-and-connected AA hypothesis***. First, we examine the alpha differential between stars and non-stars before and after Reg-FD. Second, we use structural break tests to examine whether the alpha differential between stars and non-stars diminishes after Reg-FD. In both tests, the

[25] In unreported robustness checks, we confirm that there are no reversals after a 3-day, 7-day, or 14-day holding period through the end of the first month, no reversals between the first and the second month, and between the end of the second month through the end of the first year. In addition, we analyzed portfolios that bought and held stocks with outstanding "buy" or "sell" recommendations in consecutive 2-month periods within the first year (e.g., portfolios from day 61–120, day 121–180, etc.). We find that the levels of as well as the differences between the alphas are small and statistically insignificant, confirming no reversal in these periods. Another concern is whether trading costs erode the performance differentials between AAs and non-AAs. An earlier version of our paper included detailed estimations of transactions costs. Taking transaction costs into account generally *widens* the performance differential between AAs and non-AAs because AAs tend to recommend larger, more liquid stocks. Our estimation suggests that the annual turnovers of the AA and non-AA portfolios are similar: 186 % for the AA buy portfolio and 189 % for the non-AA buy portfolio. The round-trip buy (sell) trading costs, however, are larger for the non-AA portfolios: 1.7 % (1.6 %) versus 1.1 % (1.2 %) for AAs. As an example, taking turnover and trading costs into account reduces the AAs' five-factor, 3-day buy portfolio alpha (unreported) from 2.92–2.9 % and reduces the non-AAs' (similarly estimated, 3-day portfolio) alpha from 2.11–2.07 %, thus widening the alpha differential. Effects on other portfolios are similar and confirm that transaction costs do not erode the performance differentials between AAs and non-AAs.

[26] Stickel (1995) finds that the stronger market impact of 1st-ranked AAs reverses to zero by the end of 30 days. However, he cautions that the small sample makes the inference tenuous (there were only 425 buy and 400 sell recommendations for 1st-ranked AAs in his sample). We have about 8,000 buys and 8,000 sells for top-rank AAs. In unreported robustness checks using event-study methodology (which Stickel (1995) uses), we do not find reversal by the end of the month as he documented.

Table 5 Pre-election performance results. This table reports monthly alphas based on 30-day holding period portfolios based on recommendations made by analysts *prior* to the announcement of the AA election outcomes. Panels A and B present results for buy (which include recommendation codes "strong buy" and "buy") and sell (which include recommendation codes "hold", "sell", and "strong sell") portfolios, respectively. Daily portfolio returns are calculated for the 1994–2009 period and portfolio alphas are estimated based on this daily return series. Portfolios consist of all non-tech stocks (identified from Loughran and Ritter (2004)) for which analysts issue new or revised recommendations (reiterations are excluded). Top-rank AAs are All-American analysts with either the 1st- or 2nd-place titles; Bottom-rank AAs are All-American analysts with either the 3rd-place or runner-up titles. Risk-adjusted returns are calculated using the four alternative models: CAPM, the Fama-French 3-factor model, the Carhart 4-factor model (FF + momentum), and the five-factor model, which consists of the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return

	AAs	non-AAs	AA vs. non-AA difference	Top-rank AAs	Top-rank AA vs. non-AA difference	Bottom-rank AAs	Bottom-rank AA vs. non-AA difference	Top-rank AA vs. bottom-rank AA difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Buy recommendations								
Market-adjusted alpha	2.98 %	2.29 %	0.69 %***	3.15 %	0.87 %***	2.87 %	0.59 %***	0.28 %
FF 3-factor alpha	2.82 %	2.16 %	0.66 %***	2.99 %	0.83 %***	2.73 %	0.57 %***	0.26 %
Carhart 4-factor alpha	2.90 %	2.21 %	0.68 %***	3.08 %	0.86 %***	2.79 %	0.58 %***	0.29 %
Five-factor alpha (tech-return adjusted)	2.89 %	2.20 %	0.69 %***	3.09 %	0.89 %***	2.79 %	0.58 %***	0.31 %
Panel B: Sell recommendations								
Market-adjusted alpha	−3.48 %	−2.87 %	−0.61 %***	−3.65 %	−0.78 %***	−3.33 %	−0.47 %**	−0.31 %
FF 3-factor alpha	−3.68 %	−3.06 %	−0.62 %***	−3.86 %	−0.80 %***	−3.54 %	−0.49 %**	−0.32 %
Carhart 4-factor alpha	−3.49 %	−2.84 %	−0.64 %***	−3.66 %	−0.82 %***	−3.35 %	−0.51 %**	−0.31 %
Five-factor alpha (tech-return adjusted)	−3.47 %	−2.85 %	−0.62 %***	−3.62 %	−0.77 %***	−3.34 %	−0.50 %**	−0.27 %

*, **, and *** indicate that the differences between the alphas of various analyst groups reported in columns (3), (5), (7) and (8) are significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively. *Levels* of alphas are significantly different from 0 at 1 % significance level for all analyst types and risk adjustment models used

Table 6 Return reversal results. This table compares AA and non-AAs' monthly portfolio alphas over 11 months from the end of the initial 30-day period up to the 1-year anniversary of the recommendation date. Panels A and B present results for buy (which include recommendation codes "strong buy" and "buy") and sell (which include recommendation codes "hold", "sell", and "strong sell") portfolios, respectively. Daily portfolio returns are calculated for the 1994–2009 period and portfolio alphas are estimated based on this daily return series. Portfolios consist of all non-tech stocks (identified from Loughran and Ritter (2004)) for which analysts issue new or revised recommendations (reiterations are excluded). Top-rank AAs are All-American analysts with either the 1st- or 2nd-place titles; Bottom-rank AAs are All-American analysts with either the 3rd-place or runner-up titles. Risk-adjusted returns are calculated using the four alternative models: CAPM, the Fama-French 3-factor model, the Carhart 4-factor model (FF + momentum), and the five-factor model, which consists of the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return

	AAs	non-AAs	AA vs. non-AA difference	Top-rank AAs	Top-rank AA vs. non-AA difference	Bottom-rank AAs	Bottom-rank AA vs. non-AA difference	Top-rank AA vs. bottom-rank AA difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Buy recommendations								
Market-adjusted alpha	0.11 %	0.17 %	−0.07 %	0.18 %	0.00 %	0.07 %	−0.11 %	0.11 %
FF 3-factor Alpha	−0.02 %	0.05 %	−0.08 %	0.02 %	−0.03 %	−0.05 %	−0.10 %	0.07 %
Carhart 4-factor alpha	−0.02 %	0.04 %	−0.06 %	0.02 %	−0.01 %	−0.05 %	−0.08 %	0.07 %
Five-factor alpha (tech-return adjusted)	−0.02 %	0.04 %	−0.06 %	0.02 %	−0.02 %	−0.04 %	−0.08 %	0.07 %
Panel B: Sell recommendations								
Market-adjusted alpha	0.17 %	0.22 %	−0.05 %	0.16 %	−0.06 %	0.18 %	−0.04 %	−0.02 %
FF 3-factor alpha	−0.03 %	0.02 %	−0.05 %	−0.05 %	−0.08 %	−0.01 %	−0.03 %	−0.05 %
Carhart 4-factor alpha	0.07 %	0.09 %	−0.03 %	0.03 %	−0.06 %	0.10 %	0.00 %	−0.06 %
Five-factor alpha (tech-return adjusted)	0.06 %	0.09 %	−0.03 %	0.03 %	−0.06 %	0.09 %	0.00 %	−0.07 %

*, **, and *** indicate that the differences between the alphas of various analyst groups reported in columns (3), (5), (7) and (8) significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively. *Levels* of alphas are not significantly different from 0 for any of the analyst types and risk adjustment models used

lucky-and-connected AA hypothesis predicts an erosion of star analysts' superior performance post Reg-FD whereas the ***skilled AA hypothesis*** does not.

Both tests entail breaking the sample into sensible sub-periods, which is confounded by the fact that two additional regulatory actions took place shortly after Reg-FD: In late 2002, NASD Rule 2711 came into effect which required brokerage firms to disclose the distribution of their buys, holds, and sells in their research reports; and in early 2003, the Global Settlement was reached between regulators and 12 large brokerage firms whereby $1.4 billion in fines were charged for publishing overly optimistic research.[27] Both measures were responses to the biased research scandals during the tech bubble, and had a different purpose from that of Reg-FD. But if we naively divide the sample into two periods—for example 1993–1999 as pre Reg-FD and 2000–2009 as post Reg-FD—the latter period would confound the effects of Reg-FD with those of Rule 2711 and the Settlement. Existing literature also indicates that the combination of Rule 2711 and the Settlement (introduced within a few months of one another) resulted in 2002 being an anomalous year containing a disproportionally large number of re-stated recommendations as analysts scramble to "fix" the ratio between their buys and sells so as not to appear overly optimistic.[28] Following these considerations and prior literature, we remove 2002 and define 1994–1999 as Pre-Reg-FD, 1994–2001 as Pre-Settlement, and 2003–2009 as Post-Settlement.[29]

The portfolio return results for these sub-periods are reported in Table 7. For ease of reference, the full sample period result for 1994–2009 is reported below the sub-periods. For brevity, only the five-factor alphas are reported; other models yield qualitatively similar results. Contrary to the predictions of the ***lucky-and-connected AA hypothesis****,* AAs as a whole (top-rank and bottom-rank AAs collectively) significantly outperform non-AAs in *every* sub-sample period (asterisks next to column (3) indicating statistical significance) with the exception of sells in the Post-Settlement Period. Thus Reg-FD did not seem to erode AAs' superior performance over non-AAs.

Apart from this main result, the table reveals interesting patterns in the Post-Settlement period (2003–2009). First, while alphas for buy recommendations are generally larger in this period than in earlier periods, alphas for sell recommendations are smaller. This reflects the impact of the conflicts-of-interest reforms and is consistent with prior evidence (e.g., Kadan et al. (2009)). There is also evidence of weakening of top-rank AAs' performance relative to others in this period: While they significantly outperform both non-AAs (indicated by asterisks next to column 5) and bottom-rank AAs (asterisks next to column 8) earlier on, in this period they do not. Thus, while Reg-FD did not erode top-rank AAs' performance (as they still outperform others up to 2001, which is post Reg-FD), the conflict-of-interest reforms of 2002–2003 seem to have an impact. We will revisit this point in Section 6.2 below.

[27] The 12 banks involved in the Settlement are: Bear Stearns, Credit Suisse First Boston, Deutsche Bank, Goldman Sachs, J.P. Morgan Chase, Lehman Brothers, Merrill Lynch, Morgan Stanley, Salomon Smith Barney, UBS Warburg, Piper Jaffray, and Thomas Weisel. (Thomas Weisel was added to the list in 2004). See http://www.sec.gov/news/press/2002-179.htm

[28] See, for example, Barber et al. (2006) and (2007) and Loh and Stulz (2011). Many banks also switched from a 5-grade system to a 3-grade system, which caused a spike in the number of new and re-stated recommendations issued in 2002 (Kadan et al. (2009)). In our own analysis, we found that not only 2002 contains a disproportionately large number of sell recommendations, but also that returns associated with these sell recommendations (presumably triggered by the need for regulatory compliance) were often *positive*.

[29] In unreported robustness checks we include 2002 as part of the Pre-Settlement/Rule 2711 period. The results are qualitatively unchanged from Tables 7 and 8.

Table 7 Sub-period portfolio results. This table reports monthly alphas on 30-day holding period portfolios based on AA and non-AA analyst recommendations for different sub-sample periods. Panels A and B present results for buy (which include recommendation codes "strong buy" and "buy") and sell (which include recommendation codes "hold", "sell", and "strong sell") portfolios, respectively. For each panel, results for four sample periods are reported: 1994–1999, 1994–2001, 2003–2009, and 1994–2009 (the full sample, as reported in Table 3). Portfolios consist of all non-tech stocks (identified from Loughran and Ritter (2004)) for which analysts issue new or revised recommendations (reiterations are excluded). Top-rank AAs are All-American analysts with either the 1st- or 2nd-place titles; Bottom-rank AAs are All-American analysts with either the 3rd-place or runner-up titles. Risk-adjusted returns are calculated using the five-factor model, which consists of the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return

	AAs	non-AAs	AA vs. non-AA difference	Top-rank AAs	Top-rank AA vs. non-AA difference	Bottom-rank AAs	Bottom-rank AA vs. non-AA difference	Top-rank AA vs. bottom-rank AA difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Buy recommendations								
1994–1999 (pre-regFD)	1.74 %	1.25 %	0.48 %***	2.25 %	0.99 %***	1.50 %	0.25 %	0.74 %***
1994–2001 (pre-settlement/rule 2711)	2.01 %	1.57 %	0.44 %***	2.57 %	1.00 %***	1.74 %	0.17 %	0.83 %***
2003–2009 (post-settlement/rule 2711)	3.69 %	2.92 %	0.77 %***	3.40 %	0.48 %	3.88 %	0.96 %***	−0.48 %
1994–2009 (full sample)	2.81 %	2.23 %	0.58 %***	2.92 %	0.69 %***	2.78 %	0.55 %***	0.14 %
Panel B: Sell recommendations								
1994–1999 (pre-regFD)	−3.51 %	−2.76 %	−0.74 %***	−3.66 %	−0.90 %***	−3.39 %	−0.63 %**	−0.27 %
1994-2001 (pre-settlement/rule 2711)	−4.33 %	−3.01 %	−1.32 %***	−4.46 %	−1.45 %***	−4.16 %	−1.15 %***	−0.30 %
2003–2009 (post-Settlement/Rule 2711)	−2.49 %	−2.73 %	0.24 %	−2.33 %	0.40 %	−2.62 %	0.11 %	0.29 %
1994–2009 (full sample)	−3.43 %	−2.87 %	−0.56 %***	−3.46 %	−0.59 %**	−3.38 %	−0.51 %**	−0.08 %

*, **, and *** indicate that the differences between the alphas of various analyst groups reported in columns (3), (5), (7) and (8) are significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively. *Levels* of alphas are significantly different from 0 at 1 % significance level for all analyst types and risk adjustment models used

Table 8 Structural-break tests on performance differentials between AA and non-AA analysts. This table reports performance differentials (differences in monthly portfolio alphas) between AA and non-AA analysts in different subsample periods. Portfolio construction is identical to Table 3; for brevity we report only the five-factor alpha differentials in this table. The five-factor model includes the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return. Panel A reports alpha differences in buy portfolios (which include recommendations rated "strong buy" and "buy"); Panel B reports alpha differences in sell portfolios (which include recommendations rated "hold", "sell", and "strong sell"). Pre-Reg-FD (Period 1) refers to 1994–1999; the Interim (Period 2) refers to the period between the Reg-FD and the Global Settlement & Rule 2711, namely 2000–2001; and Post-Settlement (Period 3) refers to 2003–2009. Portfolios consist of all non-tech stocks (identified from Loughran and Ritter (2004)) for which analysts issue new or updated stock recommendations (reiterations are excluded). Top-rank AAs are All-American analysts with either the 1st- or 2nd-place titles; Bottom-rank AAs are All-American analysts with either the 3rd-place or runner-up titles

	Alpha differential (%)			*p*-value for structural break test (Chow test)		
	Period 1	Period 2	Period 3	(Period 1 = Period 2)	(Period 2 = Period 3)	(Period 1+2=Period 3)
	Pre-regFD (1994–9)	Interim (2000–1)	Post-settlement & rule 2711 (2003–9)	*Ho: Pre-regFD = Interim*	*Ho: Interim = post-settlement*	*Ho: Pre-settlement = Post-settlement*
Panel A: Buy recommendations						
AA vs. non-AA	0.48 %	0.46 %	0.77 %	0.96	0.57	0.27
Top-rank AA vs. non-AA	0.99 %	1.03 %	0.48 %	0.94	0.44	0.19
Bottom-rank AA vs. non-AA	0.25 %	0.15 %	0.96 %	0.85	0.27	0.05**
Top-rank AA vs. Bottom-rank AA	0.74 %	0.88 %	−0.48 %	0.84	0.16	0.01***
Panel B: Sell recommendations						
AA vs. non-AA	−0.74 %	−2.93 %	0.24 %	0.00***	0.00***	0.00***
Top-rank AA vs. non-AA	−0.90 %	−3.03 %	0.40 %	0.01***	0.00***	0.00***
Bottom-rank AA vs. non-AA	−0.63 %	−2.58 %	0.11 %	0.00***	0.00***	0.00***
Top-rank AA vs. Bottom-rank AA	−0.27 %	−0.45 %	0.29 %	0.86	0.48	0.34

*, **, and *** indicate that the differences in the alpha differentials between various sample periods (using the Chow test for structural breaks) are statistically significant at the 10 %, 5 %, and 1 % significance level, respectively

Next we use structural break tests to examine the equality of alpha differentials across the sub-sample periods. We examine three disjoint periods: Pre-Reg-FD (Period 1, 1994–1999), Post-Reg-FD/Pre-Settlement (Period 2, 2000–2001, Interim for short), and Post-Settlement (Period 3, 2003–2009). Our null hypotheses are: (i) the Pre-Reg-FD alpha differential = the Interim alpha differential (*Ho*: Period 1 = Period 2), (ii) the Interim alpha differential = the Post-Settlement alpha differential (*Ho*: Period 2 = Period 3), and (iii) the Pre-Settlement alpha differential = the Post-Settlement alpha differential (*Ho*: Period 1+2=Period 3).

Results are reported in Table 8. In buys (Panel A), AAs outperform non-AAs by 0.48 %, 0.46 %, and 0.77 % on a monthly basis for the three sub-sample periods, respectively. These performance differentials are not statistically different from one another. Thus, consistent with Table 7, we find no evidence that Reg-FD significantly eroded AAs' superior performance. For sells (Panel B), we find a significantly *larger* performance differential between AAs and non-AAs in Period 2 (Post-Reg-FD/Pre-Settlement) than in Period 1 (Pre-Reg-FD). However, in Period 3 (Post-Settlement), AAs' performance deteriorates relative to that of non-AAs.

Overall, results in Tables 7 and 8 consistently indicate that Reg-FD did not erode AAs' performance relative to that of non-AAs in either buys or sells; in fact, the performance differential in sell recommendations significantly widened for a brief period post Reg-FD. These patterns are inconsistent with the ***lucky-and-connected AA hypothesis***, which predicts a deterioration of AA performance post Reg-FD. Interestingly, results in the two tables also point towards a significant impact of the conflicts-of-interest reforms of 2002–2003: Post 2003, there is some evidence of weakening of the top-rank AAs' performance relative to others; however, AAs collectively still outperform non-AAs (partly due to relative strengthening of bottom-rank AAs' performance).[30] We provide a more detailed analysis and discussion of the conflicts-of-interest reforms in Section 6.2.

6 Additional analysis

Collectively, results in Section 5 indicate that star analysts' opinions are worth significantly more than non-stars'; moreover, this performance differential is better explained by skill differences than either market influence or better access to management. These results suggest that institutional investors have superior ability to evaluate analysts' skills and that the AA status at least partially incorporates this information. In this section, we provide additional evidence on institutional investors' role in evaluating analyst performance. We do so by examining whether the AA status contains information above and beyond observable analyst characteristics, and by examining the special period of 2002–2003.

6.1 Does the AA status predict performance conditional on observable characteristics?

If institutional investors have superior ability to evaluate analysts, the AA status should contain information beyond other observable analyst traits. To examine this implication, we match AAs to non-AAs with similar ex-ante probabilities of being elected and compare their

[30] We also repeated these tests (unreported) separately for the banks sanctioned by the Global Settlement (primarily large banks) and other non-sanctioned banks. We find that the three main findings—namely (i) persistence of AA outperformance post Reg-FD, (ii) increase in the sell outperformance during the Interim Period and subsequent deterioration in the Post-Settlement Period, and (iii) weakening of top-rank AAs' outperformance in the Post-Settlement Period—all hold similarly for sanctioned and non-sanctioned bank analysts.

ex-post performance.[31] Specifically we compute predicted AA-election probability ($\widehat{p}$) for each analyst-year using the probit model of Table 2, Panel C. We then divide the analysts into those with high- $\widehat{p}$ (above median) and low- (below median) $\widehat{p}$ and form portfolios using recommendations made by the high-$\widehat{p}$ AAs, high-$\widehat{p}$ non-AAs, high-$\widehat{p}$ top-rank AAs, and high-$\widehat{p}$ bottom-rank AAs.[32]AAs with high ex ante election probabilities are thus matched with non-AAs with equally high ex ante election probabilities based on observable characteristics. If AAs in this comparison still beat the high-$\widehat{p}$ non-AAs, the evidence would support the view that the AA status contains institutional investors' information about which analysts' opinions are most valuable, above and beyond public knowledge.

Table 9 reports the results. Our baseline results (Table 3) for buy recommendations hold true even after sorting analysts by ex-ante election probabilities: AAs, both top- and bottom-rank sub-groups, significantly outperform non-AAs. The performance differential between AAs (column 1) and non-AAs (column 2) is about 0.4 % with various risk-adjustments, slightly lower than the unsorted results in Table 3. The sell results, however, do not survive matching on ex-ante probabilities. As expected, high-$\widehat{p}$ analysts deliver higher returns than unsorted analysts (Table 3), indicating that our probit model (and hence the observable analyst characteristics) picks up meaningful information about analysts' ability to make valuable recommendations. Thus it is natural that performance differentials after sorting on ex-ante probabilities are weaker than unsorted results. But the robust results for buy recommendations indicate that AA status contains information above and beyond observable characteristics as actual AA status *predicts* future performance even among analysts with similarly high ex-ante election probabilities.

6.2 Changes around 2002–2003

The period around 2002–2003 is a tumultuous time for sell-side research. In response to the conflicts-of-interest scandals during the tech-bubble, Rule 2711—which came into effect in 2002—put tremendous pressure on analysts to have a balanced ratio of buy and sell recommendations (previously analysts could simply withhold their opinion and not cover a firm if they had a negative view). The Global Settlement—reached in early 2003—led to budget cuts and smaller compensation packages for top analysts.[33] Our findings in Section 5.2 indicate that while Reg-FD—which took away analysts' privileged access to company management—did not significantly erode the outperformance of star analysts, these reforms in 2002–2003 clearly affected sell side research in general and star analysts in particular.[34] If institutional investors have superior ability to evaluate analysts, they need to respond to these changes, and analyzing this period is thus particularly informative about the effectiveness of the AA election process. In this section, we first hypothesize and present evidence that this period is associated with unusual shifts in the analysts' labor market. We

[31] We thank Brad Barber for suggesting this analysis.

[32] We focus on high-$\widehat{p}$ analysts because few low-$\widehat{p}$ analysts actually get elected, resulting in insufficient sample size to examine low-$\widehat{p}$ AAs.

[33] Illustrating the regulatory pressures at the time, the cover article for the 2003 AA election in *Institutional Investor* quotes an anonymous 13-year veteran analyst as saying "people are scared… that everyone's watching and ready to pounce on every little thing you say or do, whether it's the regulators, the plaintiff's lawyers, the press or even our compliance people". The article also reports investors' complaints that analysts were reluctant to take controversial stances—especially bullish ones—for fear of running afoul of regulators.

[34] Consistent with this, Kadan et al. (2009) document an overall decline in recommendation informativeness after 2003.

Table 9 Do AAs perform better ex-post than non-AAs with similar ex-ante election probability? This table reports monthly portfolio alphas of 30-day holding period portfolios based on the recommendations of AA and non-AA analysts with similar ex-ante AA election probabilities. Panels A and B present results for buy (which include recommendation codes "strong buy" and "buy") and sell (which include recommendation codes "hold", "sell", and "strong sell") portfolios, respectively. Daily portfolio returns are calculated for the 1994–2009 period and portfolio alphas are estimated based on this daily return series. To match the AA and non-AA groups on their ex-ante election probabilities, we construct predicted AA-election probability ($\widehat{p}$) for each analyst using the probit estimation results of Table 2, Panel C. We further divide the analysts into those with high- (above median) and low- (below median) $\widehat{p}$. We then form portfolios using the high-$\widehat{p}$ AAs, high-$\widehat{p}$ non-AAs, high-$\widehat{p}$ top-rank AAs, and high-$\widehat{p}$ bottom-rank AAs' stock recommendations. Portfolios consist of all non-tech stocks (identified from Loughran and Ritter (2004)) for which analysts issue new or updated stock recommendations (reiterations are excluded). Top-rank AAs are All-American analysts with either the 1st- or 2nd-place titles; Bottom-rank AAs are All-American analysts with either the 3rd-place or runner-up titles. Risk-adjusted returns are calculated using the four alternative models: CAPM, the Fama-French 3-factor model, the Carhart 4-factor model (FF + momentum), and the five-factor model, which consists of the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return

	high-*p* AAs	high-*p* non-AAs	AA vs. non-AA difference	high-*p* Top-rank AAs	Top-rank AA vs. non-AA difference	high-*p* bottom-rank AAs	Bottom-rank AA vs. non-AA difference	Top-rank AA vs. bottom-rank AA difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Buy recommendations								
Market-adjusted Alpha	2.98 %	2.56 %	0.42 %**	3.14 %	0.58 %***	2.90 %	0.33 %	0.24 %
FF 3-factor Alpha	2.83 %	2.41 %	0.42 %**	2.96 %	0.55 %***	2.78 %	0.37 %*	0.18 %
Carhart 4-factor Alpha	2.91 %	2.47 %	0.44 %***	3.06 %	0.59 %***	2.83 %	0.36 %*	0.23 %
Five-factor Alpha (tech-return adjusted)	2.91 %	2.47 %	0.44 %***	3.06 %	0.60 %***	2.83 %	0.36 %*	0.23 %
Panel B: Sell recommendations								
Market-adjusted Alpha	−3.56 %	−3.29 %	−0.27 %	−3.59 %	−0.30 %	−3.54 %	−0.25 %	−0.05 %
FF 3-factor Alpha	−3.74 %	−3.49 %	−0.25 %	−3.80 %	−0.31 %	−3.69 %	−0.20 %	−0.11 %
Carhart 4-factor Alpha	−3.55 %	−3.28 %	−0.27 %	−3.60 %	−0.32 %	−3.50 %	−0.22 %	−0.10 %
Five-factor Alpha (tech-return adjusted)	−3.55 %	−3.28 %	−0.27 %	−3.60 %	−0.32 %	−3.50 %	−0.22 %	−0.11 %

*, **, and *** indicate that the differences between the alphas of various analyst groups reported in columns (3), (5), (7), and (8) are significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively. *Levels* of alphas are significantly different from 0 at 1 % significance level for all analyst types and risk adjustment models used

Table 10 Top-rank AAs who left the profession between 2002 and 2003. This table compares the monthly alphas of 30-day holding period portfolios of the top-rank AAs who left the sell-side analyst profession between 2002 and 2003 with the baseline top-rank AAs. An analyst is considered to have left the profession if he/she no longer makes any recommendations in the following year. The buy portfolios include recommendations rated "strong buy" and "buy" and the sell portfolios include recommendations rated "hold", "sell", and "strong sell". Portfolio construction is identical to Table 3. Daily portfolio returns are calculated for the 1994–2003 period and portfolio alphas are estimated based on this daily return series. For brevity only five-factor alphas are reported in this table; the five-factor model includes the Carhart 4 factors (Market, HML, SMB, Momentum) and the tech-sector index return

	Baseline top-rank AAs (1)	Top-rank AAs who retired between 2002 and 2003 (2)	Difference (*p*-value) (3)
Buy recommendations:			
Five-factor alpha (tech-return adjusted)	2.27 %***	2.92 %***	0.06*
Sell recommendations:			
Five-factor alpha (tech-return adjusted)	−4.34 %***	−4.62 %***	0.84

*, **, and *** indicate that the reported alphas or differences are significantly different from 0 at the 10 %, 5 %, and 1 % significance level, respectively

then analyze the collective changes made by the institutional investors to the AA roster as a response to these changes.[35]

First, we posit that the reforms and related budget cuts might have made sell-side research less appealing, causing experienced, top-ranked analysts to leave the profession. In Table 10, we compare the performance of top-rank AAs who left the sell-side profession between 2002 and 2003 with top-rank AAs who remained. Consistent with our conjecture and related evidence,[36] we find that indeed the top-rank AAs who left the profession in this period had significantly better performance than other top-rank AAs (particularly in buys) prior to their departure. As a result, the remaining top-rank AA pool likely has become of lower caliber, which might explain the deterioration of their relative performance post 2003.[37]

[35] In a static setting, Chen et al. (2005) provide evidence that investors form perceptions about an analyst's ability from his track record. We go further and study the effectiveness of changes institutional investors made to the AA roster.

[36] Guan et al. (2010) show that AA analysts who depart the profession after the conflict-of-interest reforms performed better than other analysts (e.g., non-AAs) who cover the same firms prior to their departures; they do not compare the performance within the AA ranks, as we do here.

[37] In unreported analysis, we find different changes in the non-AA pool. Non-AAs leaving the profession in this period are *less* experienced than the remaining non-AAs, opposite to the pattern among top-rank AAs. Thus, the conflicts-of-interest reforms seem to have asymmetric impacts on the analysts' labor market: On the one hand, the most experienced, top-rank AAs left the profession, perhaps seeking better career options outside sell-side research; on the other hand, the least experienced non-AAs also left, possibly due to budget cuts and an overall less lucrative career prospect. Both trends are consistent with a narrowing of the performance gap between the AA and non-AA pool post Settlement. An alternative (and non-mutually exclusive) explanation for the narrowing of the performance gap is that the conflict-of-interest reforms had a sharper effect on the behavior of non-AAs than on AAs. This could be the case if the AA status mitigates conflicts-of-interest even before the reforms. Fang and Yasuda (2009) find that AA status plays a disciplining role, leading to high research quality of AAs relative to others even when the degree of conflicts was high. Thus the incremental disciplinary role of the reforms could be larger for non-AAs than for AAs. Consistent with this view, Ertimur et al. (2007) find that the positive relation between forecast accuracy and recommendation profitability strengthens after the conflict-of-interest reforms for conflicted analysts.

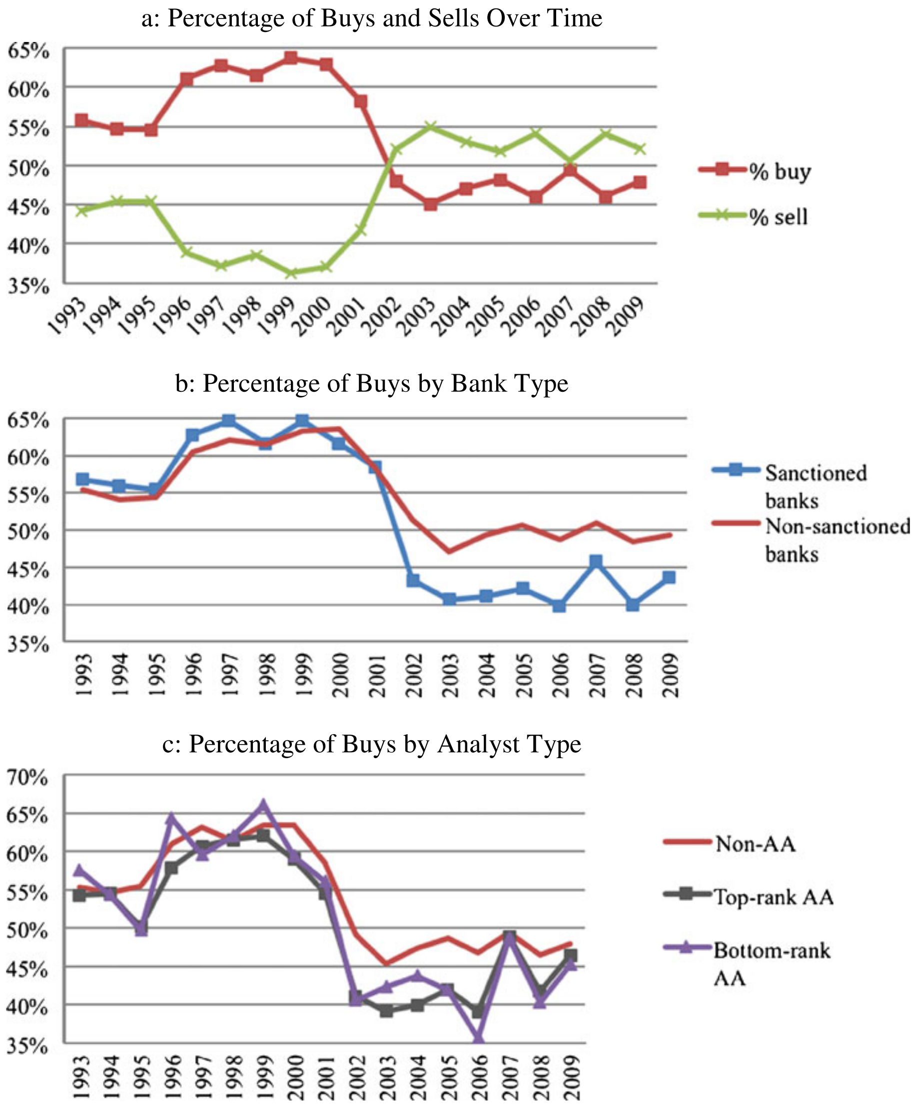

Fig. 1 Percentage of Buy Recommendations over Time. This figure plots the percentage of all recommendations that are accounted for by "buys" in each year. a) plots the percentage of buys and sells for all analysts; b) plots the percentage of buys separately for analysts employed at the Global-Settlement sanctioned and the non-sanctioned banks; and c) plots the percentage of buys separately by analysts' star status. We take the *level* of each recommendation and classify it as a "buy" if its level is either "strong buy" or "buy" (ratings 1 and 2 in the 5-point scale; 1 in the 3-point scale), and "sell" if it is "hold", "sell", or "strong sell" (ratings 3, 4, and 5 in the 5-point scale; 2 and 3 in the 3-point scale). Thus by this construction, the "buys" and "sells" in a add up to 100 % of all recommendations. This is different from the "buy" and "sell" portfolios that we construct for the alpha estimation, where we focus only on new recommendations and revisions that result in switches between the "buy" category and the "sell" category. Banks sanctioned by Global Settlement (2003) and have data in the I/B/E/S recommendation sample are: Bear Stearns, Citi Group/Salomon Smith Barney, Credit Suisse First Boston, Goldman Sachs, J. P. Morgan, Merrill Lynch, Morgan Stanley, UBS, Piper Jaffray, Deutsche Bank, and Thomas Weisel. a) Percentage of Buys and Sells Over Time. b) Percentage of Buys by Bank Type. c) Percentage of Buys by Analyst Type

Table 11 AA turnover and election patterns. This table presents statistics on AA turnovers and new elections by election year. Panel A tabulates the fraction of analysts experiencing turnover in each year. Turnover in a given year means appearing on the AA list in that year but not in the subsequent year. Panel B tabulates the fraction of first-time AAs in each year

Panel A: Percentage of analyst pool disappearing in each year among:

Year	All AAs	Top-rank AAs	Bottom-rank AAs
1993	13.0 %	6.5 %	15.0 %
1994	22.7 %	9.2 %	27.2 %
1995	11.7 %	4.4 %	15.8 %
1996	14.6 %	4.9 %	20.5 %
1997	12.2 %	5.1 %	17.2 %
1998	15.8 %	7.1 %	20.9 %
1999	19.2 %	11.6 %	23.6 %
2000	14.7 %	8.7 %	18.5 %
2001	21.0 %	12.6 %	25.7 %
2002	32.0 %	27.1 %	34.8 %
2003	22.7 %	13.3 %	28.6 %
2004	14.4 %	9.1 %	17.6 %
2005	18.7 %	11.0 %	23.0 %
2006	20.8 %	17.1 %	23.0 %
2007	26.3 %	16.8 %	32.9 %
2008	44.8 %	29.4 %	56.7 %
2009	N/A	N/A	N/A
Average:	20.3 %	12.1 %	25.1 %
Average excluding 2002:	19.5 %	11.1 %	24.4 %

Panel B: Percentage of first-time AAs in each year among:

Year	All AAs	Top-rank AAs	Bottom-rank AAs
1993	12.3 %	1.9 %	15.6 %
1994	11.4 %	5.5 %	13.3 %
1995	9.2 %	5.3 %	11.4 %
1996	11.8 %	3.3 %	17.0 %
1997	11.2 %	6.6 %	14.6 %
1998	20.8 %	8.6 %	28.0 %
1999	17.4 %	5.1 %	24.4 %
2000	14.4 %	3.6 %	21.2 %
2001	15.1 %	5.5 %	20.4 %
2002	15.3 %	2.3 %	22.6 %
2003	23.9 %	15.8 %	29.1 %
2004	14.8 %	2.7 %	21.8 %
2005	13.7 %	3.7 %	19.4 %
2006	12.9 %	2.9 %	19.0 %
2007	14.9 %	4.7 %	21.9 %
2008	17.6 %	6.4 %	26.2 %
2009	10.4 %	4.8 %	20.3 %
Average:	14.5 %	5.2 %	20.4 %
Average excluding 2003:	14.0 %	4.5 %	19.8 %

Table 12 The effectiveness of promotions and demotions around 2002–2003. This table compares the monthly alphas of 30-day holding period portfolios based on recommendations made by the following three analyst groups: (1) the baseline, actual top-rank AA group, (2) a hypothetical top-rank AA group that would obtain if the top-rank AAs demoted in 2002 and 2003 were *not* demoted (i.e., kept as top-rank AAs), and (3) a hypothetical top-rank AA group that would obtain if the non-AAs promoted in 2002 and 2003 were *not* promoted (i.e., were excluded from the top-rank AA group). Thus, portfolio (2) is portfolio (1) plus the recommendations made by the demoted top-rank AAs and portfolio (3) is portfolio (1) minus the recommendations made by the promoted non-AAs. Portfolio construction is the same as in our baseline analysis in Table 3. Daily portfolio returns are calculated for 1994–2002 (Panel A) and 2003–2009 (Panel B) and alphas are estimated from these time series

	Baseline top-rank AAs	Demoted top-rank AAs	Promoted non-AAs	Baseline vs. demoted top-rank AAs (*p*-value)	Baseline vs. promoted non-AAs (*p*-value)
Panel A: Performance before 2002					
Buy recommendations:					
Market-adjusted alpha	2.67 %***	1.73 %**	3.05 %***	0.17	0.53
FF 3-factor alpha	2.44 %***	1.53 %**	2.76 %***	0.18	0.60
Carhart 4-factor alpha	2.57 %***	1.62 %**	2.96 %***	0.17	0.52
Five-factor alpha (tech-return adjusted)	2.58 %***	1.60 %**	2.94 %***	0.15	0.55
Sell recommendations:					
Market-adjusted alpha	−4.53 %***	−3.97 %***	−6.02 %***	0.49	0.10
FF 3-factor alpha	−4.84 %***	−4.16 %***	−6.38 %***	0.40	0.11
Carhart 4-factor alpha	−4.54 %***	−3.69 %***	−5.75 %***	0.30	0.19
Five-factor alpha (tech-return adjusted)	−4.53 %***	−3.65 %***	−5.62 %***	0.28	0.24
Panel B: Performance after 2003					
Buy recommendations:					
Market-adjusted alpha	3.56 %***	3.87 %**	4.79 %***	0.79	0.12
FF 3-factor alpha	3.39 %***	3.68 %**	4.65 %***	0.82	0.11
Carhart 4-factor alpha	3.39 %***	3.63 %**	4.63 %***	0.83	0.11
Five-factor alpha (tech-return adjusted)	3.40 %***	3.69 %**	4.65 %***	0.81	0.11
Sell recommendations:					
Market-adjusted alpha	−2.14 %***	−0.75 %	−1.26 %	0.29	0.38
FF 3-factor alpha	−2.32 %***	−0.98 %	−1.48 %	0.28	0.38
Carhart 4-factor alpha	−2.32 %***	−0.98 %	−1.46 %	0.25	0.38
Five-factor alpha (tech-return adjusted)	−2.33 %***	−0.97 %	−1.46 %	0.25	0.38

*, **, *** indicate statistical significance at the 10 %, 5 %, and 1 % level, respectively

Second, the remaining analysts might have yielded to the pressure from Rule 2711 by making big adjustments to the ratio between bullish and bearish calls, leading to a relative paucity of good buy recommendations. Figure 1 offers a visual illustration of these adjustments. In 2001, about 60 % of recommendations are buys; by 2003, the ratio drops to below 50 %.[38] AAs (both top-rank and bottom-rank ones) and analysts working at the banks sanctioned by the Settlement make even bigger adjustments, reducing the fraction of their buys to 40 % of all recommendations.

If institutional investors have superior ability to evaluate analysts, we expect them to make changes to the AA roster as a response to the regulation-related shifts in analysts' labor market in 2002–2003. Such changes may not completely offset the negative impact of the departures of talented analysts from the profession, but they should partially dampen such impacts in the direction of preserving the AA pool's performance. Table 11 tabulates annual turnover statistics of the AA pool, and shows that indeed the AA pool, and especially the top-rank AA pool, experienced unusually high turnover around 2002–2003.[39] In 2002, for example, 27 % of the top-rank AA pool made their last appearance on the AA list, which is nearly 2.5 times the average of 11 % for other years. Correspondingly, in 2003 a disproportionally high fraction—nearly 16 %—of top-rank AA titles was awarded to first-time AAs, more than 3 times the 4.5 % average for other years. In comparison, the changes in turnover rates among the bottom-rank AAs were less dramatic.

The key question pertinent to institutional investor's role in analyst evaluation is the following: Faced with regulatory pressures and labor market disruptions, were institutional investors—who elect the AAs—able to respond in a way that helped preserve the AA pool's performance? In other words, were the promotions/demotions made to the AA pool during this period effective?

To answer this question, we study the performances of a) the top-rank AAs who were "demoted" to non-AAs in 2002–2003 and b) the non-AAs who were "promoted" to top-rank status during the same period.[40] Table 12 compares the performances of these analysts with that of the baseline top-rank AAs both before 2002 and after 2003. We find that the newly-promoted top-rank AAs performed better than the baseline group in both buys and sells before 2002; in contrast, the demoted top-rank AAs performed worse than the baseline group in both buys and sells. Although the results are not statistically significant, this is likely due to the small sample size.[41] Notably, after 2003, the promoted analysts showed stellar performance in buys, suggesting that the ability to make sound bullish calls (which became rarer) were particularly valued by the institutional investors in the Post-Settlement period. Importantly, the performance of the promoted analysts is superior to that of the

[38] In constructing Fig. 1, we take the *level* of each recommendation and classify it as a "buy" if its level is either "strong buy" or "buy" (ratings 1 and 2 in the 5-point scale; 1 in the 3-point scale), and "sell" if it is "hold", "sell", or "strong sell" (ratings 3, 4, and 5 in the 5-point scale; 2 and 3 in the 3-point scale). Thus by this construction, the "buys" and "sells" in Fig. 1a add up to 100 % of all recommendations. This is different from the "buy" and "sell" portfolios that we construct for the alpha estimation, where we focus only on new recommendations and revisions that result in switches between the "buy" category and the "sell" category.

[39] We define turnover as the analyst disappearing from the AA list. This includes either being demoted to non-AA status or leaving the profession entirely. In a related study, Bagnoli et al. (2008) calculates retirement rates and report that AA retirements rose in 2000 around the passage of Reg-FD, and returned to the Pre-Reg-FD level in 2001 and 2002.

[40] We also examined promotions/demotions between top-rank AA positions and bottom-rank AA positions. Results for these comparisons are qualitatively similar but weaker than the reported results and generally insignificant.

[41] Both demotions from top-rank AA to non-AA and promotions from non-AA to top-rank AA involve fewer than 50 analysts.

demoted group in both buys and sells. Collectively, these results suggest that, conditional on top talents leaving the profession (which investors had no control over), the reshuffling done by institutional investors to the AA roster during 2002–2003 was largely rational and helped preserve the performance of the AA pool. Had these promotion/demotion decisions not been made, the AA pool overall would have performed worse than it did post-Settlement.

7 Conclusion

Using an extensive dataset on stock recommendations between 1994 and 2009, we examine the relation between analysts' star status (proxied by analysts' AA titles) and the investment value of their stock recommendations, and a number of hypotheses regarding the sources of star analysts' performance.

We find that stars' opinions are worth significantly more than those of non-stars: For investors with advance access to analyst information, risk-adjusted returns of AAs' buy and sell recommendations exceed those of non-AAs by 0.6 % on a monthly basis. For investors without such access, top-rank AAs' buy recommendations still significantly outperform others by about 0.3 % on a monthly, risk-adjusted basis. These performance differentials exist both before *and* after AAs are elected, are not explained by initial announcement effects, and are not significantly eroded by Reg-FD, which presumably reduced star analysts' privileged information access to company management.

These results suggest that AAs outperformance is not entirely due to luck, market influence, or better access to company management. Instead, they suggest that skill differences among analysts exist and the AA outperformance at least partially reflects their superior skill. We provide additional evidence that institutional investors actively evaluate analysts. First, among analysts whose observable traits predict high ex-ante probabilities of being elected as stars, we find that those ex-post winners of the star title perform significantly better than ex-post non-stars. Thus the AA-election process picks up otherwise unobserved characteristics related to analyst performance. Second, we analyze institutional investors' responses to shifts in sell-side analysts' labor market that resulted from the conflicts-of-interest reforms around 2002–2003. We show that those analysts promoted to star status during this period were better performers both prior to 2002 and after 2003 (especially in buys), while those demoted from star status were in fact under-performers. Collectively, results in this paper suggest that skill difference at least partially explains performance differences between elected star analysts and others. While client investors with advance access are positioned to benefit from the recommendations of star analysts, other investors' ability to do so is more limited due to their timing disadvantage.

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