Does analyst ranking affect how informative target prices are to institutional investors?[1]

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ABSTRACT

Evidence shows that market participants value analysts' target prices. There is limited evidence, however, on how target price revisions influence investors' decisions. I examine whether analyst ranking status affects institutional investors' decisions to incorporate target price information into their investment strategies. This examination is relevant to the economic question: Does analyst reputation mitigate or exacerbate the conflicts of interest that analysts face? Consistent with institutional investor trades being based on superior information, I observe differences in the information content of target price revisions by star and non-star analysts. Additionally, a duration analysis shows that low target price quality significantly increases the hazard of institutional investors not voting analysts as 'stars'.

JEL classification: G11, G14, G29, C30, C41.

Keywords: analyst forecast, target price, institutional investor, institutional ownership.

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1. *Introduction*

A well-established result in the literature is that analyst coverage affects a stock's marketability. High quality analyst reports improve a company's information environment and provide assurance to investors that analyst research outputs are credible. Investor confidence in analyst reports translates into potential rewards to analysts in their career development. Most importantly, institutional investors scrutinize analyst research and assess its value to produce an analyst ranking, an indicator of equity research quality. It is not surprising then that analysts are conscious of how their forecast disclosures affect their reputations. However, there is a limited understanding in the literature of whether the market appreciates analyst target prices and whether institutional investors pay attention to analyst target prices, the equity research output most comparable to market prices. Bradshaw et al. (2012) argue that sophisticated investors do not trust the credibility of analyst target prices. They find no evidence of differential target price forecasting ability among analysts and conclude that analysts have weak incentives to forecast accurate target prices because their target price revisions are not subject to market scrutiny. They argue that inaccurate target price forecasts are unlikely to jeopardize analyst reputation and compensation. They further argue that target price accuracy is not systematically tracked by the analyst firms or their clients. On the other hand, earnings forecast and recommendation metrics are tracked by various companies provide periodical raking of analysts on the accuracy of those metrics. However, the lack of tangible evidence on target prices being tracked does not necessarily imply that target price performance is not being assessed and consequently that target prices are not useful to investors. The examination of Bradshaw et al. (2012) does not distinguish between star and non-star analyst target price revisions. It is, therefore, inconclusive whether or not analyst target price revisions are credible and useful to investors.

A number of distortions can bias the objectivity of analyst target prices and other analyst forecasts. Examples of distortions include analysts herding on the consensus to build and preserve reputation (Hong et al., 2000), biasing forecasts upward to stay well-connected with corporate clients and gain access to information (Lim, 2001), and biasing forecasts to generate underwriting and brokerage business for investment banks. Yet, the literature documents that analyst target prices are an important source of information to market participants. Brav and Lehavy (2003) and Asquith et al. (2005) find significant market responses to analyst target prices. Asquith et al. (2005) show that the price response to a target price revision is higher and more persistent than the response to an equal percentage EPS forecast revision. Using Italian data, Bianchini et al. (2008) develop investment portfolio strategies based on analyst target price forecasts and show that they generate significant positive abnormal returns, with the source of this profitability being the strong positive relation between target price implied returns and the portfolio return. As there is no consensus in the literature on whether analyst target prices are only sales hype, I delve more deeply into the phenomenon. Specifically, I examine whether analyst ranking affects the role of target prices in informing the investment decisions of the most sophisticated investors, namely institutional investors. Additionally, I examine whether target price quality affects institutional investors decisions to vote analysts 'star'.

This study is the first to explore empirically the effect of analyst ranking on how informative target prices are to institutional investors. This investigation is important for two main reasons. First, the analysis informs our general understanding of the role of target prices, by exploring whether target prices are aimed at sophisticated investors. Institutional investors play a key role in capital markets and their information acquisition preferences directly affect stock price efficiency. For example, if they value the target price revisions of star analysts, the most visible analysts in the market, then target prices of star analysts play an important role in determining stock prices. Early evidence documents that institutional investors trade in the direction of analyst stock recommendations (He et al., 2005; Chen and Cheng, 2006; Oppenheimer and Sun, 2009). Lin and Tan (2011) report evidence of target price forecasts providing institutional investors with information not already reflected in other analyst forecasts and prevailing market prices. They find that consensus target price revisions have explanatory power for changes in institutional ownership incremental to changes in EPS and recommendation forecasts and after controlling for other factors determining institutional trading preferences. This is consistent with previous results in the literature that target prices contain information beyond that in stock recommendations and earnings forecasts. However, Lin and Tan (2011) draw inferences about changes in institutional ownership using changes in the consensus target price and their approach assumes that institutional investors do not distinguish revisions that provide new information from revisions that merely move toward the consensus. The second reason this study is important is that it is relevant for the debate on whether analyst reputation mitigates or exacerbates the conflicts of interest that analysts face. If star analysts are more informative than other analysts when revising their target prices then we should observe significant changes in institutional ownership associated with revisions by these analysts. Moreover, if target price quality matters to institutional investors, analysts with lower target price quality should be prone to higher risks of losing their star status. The findings therefore contribute to the analyst forecasting literature concerned with analyst conflicts of interest and their implications for the quality of their equity research.

To examine whether institutional investor responses to the information in target price revisions depends on analyst ranking, I define analyst star status based on the *Institutional Investor* annual star ranking. Analyst star ranking is a highly regarded designation in the capital market. Every spring, the *Institutional Investor* magazine sends out surveys to institutional investors such as portfolio managers, research directors, and chief investment officers of the world's largest pension funds, hedge funds, and mutual funds, asking them to rank analysts in each industry sector based on any criteria they see fit. Star analysts typically have higher public recognition, more experience, work for larger brokerage houses, cover larger stocks, and make more frequent revisions (Leone and Wu, 2007; Emery and Li, 2009). *Institutional Investor* weights the votes for each analyst by the size of the investor (the amount of money under management) and publishes the assigned All-America Research Team ranks every year in its October issue. Analysts and brokerage houses value this ranking highly. For analysts, a star ranking normally maps into career prospects. As new stars become visible, other banks try to attract them with high salaries (Hong and Kubik, 2003; Hong et al., 2000). For investment banks, the number of star analysts in their research departments adds to the bank's prestige and attracts more underwriting business (Irvine, 2004; Cowen et al., 2006; Jackson, 2005). It also attracts more brokerage business since institutional investors allocate their trading commissions among brokerage firms according to which analysts provide more informative research (Ljungqvist et al., 2007).

Analyst star ranking is not only a key ingredient of analyst career success but also a significant determinant of the value of analyst opinion in the market. Research by Stickel (1992), Park and Stice (2000), and Jackson (2005) suggests that high reputation analysts have a greater impact on investors' decisions. Additionally, star analysts issue more accurate EPS forecasts than non-star analysts and their recommendations generate larger returns (Stickel, 1992; Desai et al., 2000; Leone and Wu, 2007; Gleason and Lee, 2003; Clarke et al., 2010; Fang and Yasuda, 2010). Jackson (2005) and Fang and Yasuda (2009) find evidence of analyst reputation being effective in reducing the conflicts of interest analysts face. On the other hand, Clarke et al. (2010) report that institutional investor reaction is more significant to downgrades by star analysts than by non-star analysts. They find that institutional investors trade in the direction of upgrade recommendations only when they differ from the consensus and they find no significant evidence that institutional investors pay attention to upgrade recommendations by star analysts. Their results suggest that institutional investors are more likely to follow recommendations by star analysts only when the recommendations are negative. Moreover, analyst ranking status comes not only from forecast quality but also from building and maintaining strong ties with institutional investors and company management. An analyst's job is more complex and personal than simply writing reports and rating stocks. Sell-side analysts have to market themselves and their research to institutional investors. To enhance their ranking status, analysts regularly communicate with institutional clients and respond quickly to their queries. If they don't, analysts reduce the chance of their names appearing in the *Institutional Investor* survey sheet. Emery and Li (2009) report that analyst visibility dominates forecast accuracy in determining an analyst's chances of being ranked a star. Gleason and Lee (2003) find that investors do not make a sufficient distinction between analyst revisions that bring new information to the market and those that herd on the consensus. Bonner et al. (2007) show that investor familiarity with analysts' names rather than their superior performance is more influential in determining market reaction. Yet, the evidence on the effect of analyst reputation on the quality and usefulness of their research output is limited to EPS forecasts and stock recommendations.

Consistent with institutional investors trading on superior information, I expect to observe differences in the value of information conveyed by target price revisions of star and non-star analysts. In choosing an appropriate research design to test how informative target prices are to institutional investors, it is important to note that analyst forecast revisions affect institutional investor behavior because the information they supply influences institutional investment decisions and institutional investors also affect analyst behavior by influencing analyst coverage decisions (O'Brien and Bhushan, 1990; Ackert and Athanassakos, 2003). In the presence of endogeneity, arising from this simultaneity, OLS estimation is biased and inconsistent. I therefore use a research design that combines duration analysis with Heckman's two-stage model to control for analyst differential target price revision selection and to assess the impact of target price revisions by star and non-star analysts on the change in institutional ownership. I conduct this analysis using a sample of analyst reports covering

US stocks during 2000–2009.[3] The evidence I present shows that analyst behavior and target price disclosure decisions are sensitive to analyst reputation, and by implication, to investor perceptions of the quality of equity research.

The analysis shows that the impact of target price revisions on the change in institutional ownership is significant. I also find significant differences in the relationship between institutional ownership changes and target price revisions by star and non-star analysts. I find that institutional investors generally respond positively to target price revisions by star analysts while the association between institutional ownership changes and target price revisions by non-star analysts is significantly negative. The results imply that institutional investors find target price revisions by star analysts informative. This also suggests that it is important to control for analyst ranking status when examining the information content of target prices to institutional investors. To further validate the findings, I conduct a duration analysis to examine the effect of analyst target price quality on the likelihood of a star analyst losing star status. I find that target price quality significantly influences the likelihood of analysts losing their star status (i.e., institutional investors penalize analysts for low target price quality).

The findings in this study have important implications for the analyst literature. I highlight the importance of adjusting for analyst heterogeneity when examining the information content of analyst target prices. The previous literature examining the relationship between institutional ownership and analyst forecasts aggregates analyst forecasts and examines the relation between institutional behavior and the information content of the consensus forecast. I decompose the forecast consensus by analyst star status to control for analyst incentives. Additionally, the paper adds, in a broader sense, to the literature concerned with the economic importance of analyst reputation. The results have important implications for analysts as they show that the quality of their target prices influences career outcomes. The findings are important to investors because they show that investors can increase their confidence in the quality of star analyst target prices.

2. *Research hypotheses*

[3] Results are not sensitive to adding observations from the year 1999, the first year target price data are available on I/B/E/S. I exclude those observations from the main analysis because the number of target price observations in 1999 is very small relative to other years in the sample.

The literature studying the link between analyst and institutional behavior documents that institutional investors find analyst stock recommendation revisions informative (Chen and Cheng, 2006; Oppenheimer and Sun, 2009). This literature also finds that institutional investors distinguish between recommendation revisions issued by star and non-star analysts. Clarke et al. (2010) use daily institutional ownership levels to examine the reaction of institutional investors to analyst recommendations conditional on the quality of the recommendation. They find a significant relationship between changes in institutional ownership and analyst reputation. Their finding is consistent with the literature studying analysts' communication and information gathering behavior that highlights the importance of controlling for analyst incentives (Hayes, 1998; Morgan and Stocken, 2003; Fischer and Stocken, 2010). This research finds that analysts' incentives influence their information gathering decisions and communication with investors. Trueman (1994) finds that high ability analysts overweight public information signals relative to private signals in order to maintain reputation. Jackson (2005) shows that analysts favor building up long-term reputation over the potential short-term gains from generating more trading commission for their banks.

The analyst literature also draws a link between analyst target prices and their stock recommendations. The general understanding in the literature is that analysts make stock valuations to derive or justify their stock recommendations. For example, Bradshaw (2002) finds that there is a relationship between the direction of analyst stock recommendations and the degree of overpricing or underpricing implied by analyst target prices. He finds that analysts are more likely to make larger target price revisions when issuing more positive recommendations. Given this relationship between analyst target prices and recommendation revisions, in addition to the incremental information content of target prices over stock recommendations (e.g., Brav and Lehavy, 2003; Asquith et al., 2005), it seems unlikely that institutional investors trade upon analyst stock recommendations alone and do not trade upon the information contained in target prices. It also seems unlikely that institutional investors fail to recognize the incremental information of star over non-star target price revisions when they make a clear distinction between star and non-star analysts when following recommendations. However, stock recommendations are relatively sticky variables whereas target prices are relatively more volatile. Changes in target prices happen a lot more often than changes in recommendations. Moreover, target prices provide information on the expected absolute return, whereas recommendations are an indication of the relative attractiveness of the stock. Therefore, it is possible that target price revisions are uninformative or less informative than stock recommendations to institutional investors. No prior research examines whether institutional investors distinguish between target price revisions by star and non-star analysts. This study fills this gap and addresses the important economic question: Does analyst ranking influence the degree to which target prices influence the trading of institutional investors?

Using consensus target prices does not provide unambiguous inferences about the relation between institutional ownership changes and analyst forecasting behavior because target price revisions by some analysts contain valuable information incremental to revisions by other analysts. Moreover, institutional investors are likely to trade on valuable revisions rather than on the consensus forecast. While institutional investors cannot observe the information analysts gather, they can compare analyst forecasts to the consensus and form a view on whether an analyst report adds value. Institutional investors are unlikely to blindly follow the consensus target price forecast. They know that, for a variety of reasons, analysts feel pressure to bias their forecasts upward. They are also better placed than retail investors to estimate the bias in analyst forecasts and make investment decisions based on valuable information. Further support for the conjecture that some analysts' target price revisions explain institutional ownership changes better than the consensus target price forecast comes from the fact that analysts choose when to disseminate valuable information through their forecasts. This is evident from Frankel et al.'s (2006) finding that the information content of analyst forecasts increases with increases in return volatility and trading volume. Frankel et al. interpret these findings as follows (p. 31):

> This result suggests that analysts provide more information when profit opportunities for informed traders increase. Under these circumstances, I expect investors to seek more information from analysts. My result is thus consistent with analysts responding to increased investor demand for private information.

This implies that analysts choose when to issue valuable revisions. It also implies that analysts provide information when there is a demand for it and when they are likely to realize benefits from meeting this demand, higher than the costs of information processing. Chen and Jiang's (2005) evidence on optimistic weighting, also motivates this reasoning. According to this phenomenon, analysts place more weight on private than on public information when issuing good news relative to the consensus forecast and more weight on public than on private information when issuing bad news relative to the market consensus. They also find that this phenomenon is less common among less experienced analysts, who have higher reputational concerns due to the high potential cost associated with optimistic weighting.

I further argue that analyst ranking status determines the value of the information analysts disclose through target prices. Disclosure quality can be a voluntary choice of the analyst or a response to increased institutional investor demand for information. The demand for informative research increases for stocks with high institutional ownership (Frankel et al., 2006). Ljungqvist et al. (2007) provide evidence that equity analysts are less likely to bias their forecasts upward for stocks that are highly visible to institutional investors. I extend this to argue that analysts with differing star status have different abilities and incentives to make informative target price revisions and attract market attention. Hence, I expect to see differences between the effect of target price revisions by star and non-star analysts on the change in institutional ownership. Moreover, if institutional investors follow the revisions of star analysts then this should signal that target price revisions are not attention-grabbing events. I therefore test the following hypothesis,

H1: *The change in institutional ownership is positively related to changes in target price revisions by star analysts.*

Further, I investigate whether analyst target prices are subject to market scrutiny. I explore whether star analysts face pressure to conform to the consensus when making target price revisions in order to protect their star status. If I find evidence that target price quality does not affect the likelihood of analysts gaining their star status then star analysts may have incentives to issue biased or uninformative revisions. To examine this reasoning, I test the following hypothesis,

H2: *Analyst target price quality affects the likelihood of acquiring analyst star status.*

3. Sample

My sample consists of US public companies receiving equity analyst coverage between 2000 and 2009. I obtain data on analyst target price forecasts, earnings forecasts and stock recommendations from the I/B/E/S database. I exclude observations that do not include a target price forecast. I also exclude observations that do not disclose the identity of the analyst issuing the forecast because it is not possible to identify whether the analyst making this forecasts is a star analyst or not. I collect data on analyst rankings from *Institutional Investor*.

I match this data with the analyst report observations. If analysts are listed in the All-America Team, they are classified as star analysts in all research report observations following the *Institutional Investor* October issue until the next October issue.[4] To construct the other variables in the analysis, I collect daily stock price data from CRSP, quarterly accounting indicator data and earnings announcements from the CRSP/Compustat merged database and data on quarterly institutional common stock holdings from the Thomson-Reuters Institutional Holdings (13F) Database.[5] The final sample comprises 52,483 quarterly changes in institutional holding observations for 2,646 public US stocks. I use this data to model the relation between analyst target price revisions and changes in institutional ownership using Heckman's two stage selection model combined with a duration analysis that models the analyst forecast revision events. I conduct a second duration analysis that models analyst star ranking events. For this analysis, I decompose my sample into analyst-level annual observations. The decomposed sample covers the same sample of US public companies that receive equity analyst coverage between 2000 and 2009. The sample consists of 549 research departments and 7,527 analysts. This analyst-level sample comprises a total of 352,198 observations (including 90,702 analyst ex-star ranking event observations).

4. Research design and model

Not all institutional quarterly ownership change observations in my sample are accompanied by target price revisions by star analysts.[6] This observation is consistent with observations in the literature that analysts withhold disclosing target prices in almost 30% of their reports (Asquith et al., 2005; Brav and Lehavy, 2003; Bradshaw, 2002). I expect analysts' decisions to make target price revisions to be endogenous, resulting in a selection bias. I employ Heckman's two stage analysis to examine the relationship between the information content of target prices by star and non-star analysts and changes in institutional ownership. This research design makes it possible to correct for selection bias. This correction is necessary because the relationship between institutional ownership changes and analyst revisions is likely to depend on the analyst decision to make a revision. The literature documents this interrelation between analyst forecasting behavior and institutional interest (Schipper, 1991;

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[4] The *Institutional Investor* All-America team ranking classification includes first, second, and third team analysts as well as runners up.

[5] This database was formerly the CDA/Spectrum 34 database. It contains institutional ownership information reported on Form 13F filed with the SEC. Institutional owners are managers with $100 million or more in Assets Under Management.

[6] Only 21,551 of the 52,483 quarterly changes in institutional holdings observations are accompanied by target price revisions by star analysts.

Ackert and Athanassakos, 1997, 2003; Das, et al., 1998). Analysts issue more informative forecasts for firms that are highly visible to institutional investors (Frankel et al., 2006). Additionally, the presence of institutional investors influences analysts' private information dissemination decisions by increasing analyst following (Bhushan, 1989). Similarly, the information disseminated by analysts in their reports may influence the behavior of institutional investors. Positive analyst forecast revisions are associated with increases in institutional holdings (Ackert and Athanassakos, 2003). Consequently, institutional ownership and analyst coverage are jointly determined (O'Brien and Bhushan, 1990; Ackert and Athanassakos, 2003).

I estimate the first stage of the model using a duration analysis rather than a probit model.[7] I conduct the duration analysis to analyze analyst decisions to issue or withhold target price revision in a particular quarter. To define the duration variable for a target price observation i occurring in quarter t, I aggregate all analyst reports covering stock j for the two groups of star and non-star revisions. I then calculate the duration variable as the period starting with the most recent revision issued by the analyst group (star or non-star) to cover stock j at time $t-1$ and ending at time t. The duration variable therefore captures the time it takes for an analyst group to revise their previous forecast. After defining the time variable, duration analysis specifies the probability distribution of the variable using a hazard function. The hazard function gives the probability that analysts who have made previous forecasts, revise their forecasts at a specific point in time. Estimating the hazard function determines the effect of the covariates on the average number of days between revisions and the probability of occurrence of the revision. Analyzing duration data using ordinary least-squares (OLS) and logistic regressions is inappropriate for two reasons. First, the alternative models cannot allow for the inclusion of time varying covariates. Second, duration data are often subject to censoring. If a group of analysts does not provide any target price revisions for a particular company in a quarter, the observation is censored. Duration models can handle censored data while the two alternative methods waste information by dropping censored observations.[8] In my setting, retaining censored information is important to control for selection bias. Moreover, using a static model ignores the fact that analyst decisions to revise target prices represent the termination of a continuous spell of adopting a target price forecast, a spell that

[7] Sensitivity tests show that the results are not different using a probit model. However, probit estimation assumes a static model and does not take account of differences in the time each analyst takes to revise an earlier forecast. Duration analysis is more flexible in the way that covariates affect event outcomes.

[8] Although it is possible to adjust linear regression models to deal with censored data, duration models offer better ways of handling censoring of high durations (Berg, 2001, p. 3388).

is of varying length for each analyst group. Duration analysis overcomes this problem by explicitly controlling for time and allowing for time varying covariates. It accounts for the fact that analysts' decisions and their tendency to revise their forecasts change through time. In other words, duration analysis offers a tool to assess empirical changes using continuously measured variables. The duration model uses all available information to determine the probability of an analyst group making a forecast revision at each point in time. Conducting such a comprehensive examination can help control for the endogeneity of the analyst target price revision decision. I use recurrent event data to improve the estimation, overcome any identification problems and efficiently handle the task of defining censored observations.

Duration analysis requires specifying the underlying distribution of the hazard function. As there is no strong argument for a specific parametric model, I use a semi-parametric (or proportional) model, which only specifies a functional form for the influence of the covariates and leaves the shape of the hazard rate unspecified. I estimates Cox's proportional hazard model, which takes the following form,

$$h\left(t \mid N(t), X\right) = \lambda_0(t)\exp\left(X'\beta\right) \tag{1}$$

In equation (1), $\lambda_0\left(t\right)$ is the baseline hazard, which is the rate of occurrence of the event (e.g., a target price revision by star analysts) when all explanatory variables are equal to zero. The vector X contains all covariates determining forecast revision decisions and β is a vector of parameters. The term $N(t)$ counts the number of revisions issued by each analyst group before the end of the sample period. The effect of the covariates is to induce proportional shifts in the hazard rate but not to change its shape. The advantage of analyzing duration data using Cox's model is that it allows for semi-parametric estimation of β without the need to specify the functional form of the baseline hazard. This is an advantage because misspecification of the baseline hazard results in inconsistent parameter estimates (Cameron and Trivedi, 2005). Hence, the model is convenient when testing hypotheses only requires information on the magnitude and direction of the effects of observed covariates, controlling for time dependence.

Little is known about the determinants of analyst target price disclosure.[9] When making disclosure decisions, analysts may consider the effect of forecast disclosure on their reputation, career prospects, the business that their revisions generate for their investment banks and brokers, their relationships with companies, their performance relative to other analysts, etc. I construct a duration model to examine the determinants of analyst decisions to revise target prices in a specific quarter. This analysis contributes to our knowledge of the drivers of analyst decisions. It also serves as a guide for future research developing advanced methods for assessing the quality of analyst reports. I estimate the following duration model, at the analyst level,[10]

$$h_i(t \mid N(t), X) = h_0(t)\exp\Big(\beta_1 Top + \beta_2 \ln Shrs + \beta_3 Mom + \beta_4 Neg + \beta_5 Neg \times Mom + \beta_6 Beta + \beta_7 SD + \beta_8 \mathrm{Ln}Anlys + \beta_9 \mathrm{L}inst + \sum_{i=1}^{47} \pi_i I_i\Big) \qquad (2)$$

The underlying assumption of the model in equation (2) is that the analyst forecast revision decision depends on the benefit the analyst expects to generate from making the revision as well as market related factors.[11] The number of large institutional investors holding shares in the firm the analyst is covering (*Top*) is likely to influence analysts' decisions to revise their forecasts. Institutional investors are the primary users of analysts' reports. If analysts consider the presence of institutional investors when revising target prices, it is likely that the importance of the institutional investor influences the revision. Institutional investor votes for analysts are weighted by the size of funds under management. Therefore, larger institutional investors have more power to influence analyst rankings. It is, therefore, more plausible that analysts alter their forecasting behavior when covering stocks held by the largest institutions. Hence, I expect analysts to have greater incentives to revise forecasts for stocks primarily owned by large institutions. Information about the amount of money under management or the size of the institution is not readily available. Therefore, to investigate this conjecture, similar to Ljungqvist et al. (2007), I first identify the top 100 institutional investors in the market ranked by the total value of their equity holdings in the last quarter of the year prior to the beginning of my sample. I count how many of these investors hold stocks in each firm

[9] The most relevant literature is an attempt to study the determinants of analysts' revision frequency, which is the number of revisions analysts make within a specific time period (e.g., Holden and Stuerke, 2008) and a study of the determinants of analyst following (O'Brien and Bhushan, 1990).
[10] I use multivariate duration data because more than one event may occur for the same analyst. The event times are therefore correlated within analyst clusters, violating the independence of event times assumption required in traditional duration analysis.
[11] Table 1 provides precise variable definitions.

each quarter.[12] The covariate $\ln Shares$ is the natural log of the total number of shares outstanding at the beginning of the current quarter. Positive cumulative stock returns (*Mom)*, negative returns (*Neg*), and the interaction between them (*Neg* × *Mom*) capture the extent to which revisions are associated with new public information.[13] Beta (*Beta*) and the standard deviation of residuals (*SD*) control for systematic and unsystematic risks of the stock. I also control for the number of analysts following in the previous quarter (L*nAnlys*) and the level of institutional ownership in the previous quarter (L*inst*) because I expect revision decisions to depend on whether or not they are for companies that are highly visible to institutional investors. Last, industry dummies (*I*) capture industry-related differences in analyst behavior. I expect a positive association between analyst revision decisions, lagged institutional ownership, lagged analyst following, and number of shares outstanding.

I treat changes in institutional ownership and analyst decisions to revise target prices as endogenous and estimate the second stage of Heckman's model using the OLS regression equation (3) below to model institutional ownership change and analyst target price revisions. I estimate the following model of the relation between changes in institutional ownership and changes in analyst target price forecasts for the two analyst ranking groups.

$$\begin{aligned}\Delta inst = {} & \beta_0 + \beta_1 \Delta TP_{star} + \beta_2 \Delta TP_{non} + \beta_3 \Delta EPS + \beta_4 \Delta REC + \beta_5 Mom + \beta_6 \Delta Beta \\ & + \beta_7 \Delta SD + \beta_8 \Delta Vol + \beta_9 \Delta Div + \beta_{10} PE + \beta_{11} BM + \beta_{12} \ln Cap \\ & + \beta_{13} \mathrm{L}inst + \beta_{14} ROE + \beta_{15} \Delta nStar + \beta_{16} Lev + \beta_{17} Turn + \sum_{i=2}^{4} \beta_i Q_i \\ & + \sum_{i=2000}^{2010} \beta_i Y_i + invMills + \varepsilon \end{aligned} \tag{3}$$

To examine the trading behavior of institutional investors, I use a conventional measure of institutional ownership change (e.g., Jiang, 2010; Lin and Tan, 2011), the change in institutional investor holdings at the end of the quarter ($\Delta inst$). The main right-side variables in equation (3) are the two changes in analyst target price consensus for the two ranking groups, ΔTP_{star} and ΔTP_{non}, corresponding to changes in target price revisions by star and non-star analysts. For each analyst–firm, I use the most recent forecast issued within the quarter to eliminate the impact of stale forecasts and compute the analyst target price

[12] The results hold when I use the aggregate size (instead of the aggregate count) of the top 100 investors in each firm in each quarter, similar to Ljungqvist et al. (2007).

[13] I split stock returns into positive and negative returns to capture the different reactions of analysts to good news and bad news, where stock returns proxy for the type of news. Basu (1997) uses this technique.

consensus for each ranking status group as the mean of the latest target prices issued by analysts in a specific ranking group for each firm.[14] I calculate the change in target price as the difference in the average target prices in quarters t and $t-1$ scaled by the average target price in quarter $t-1$. The choice of control variables in equation (3) is motivated by earlier literature on the determinants of institutional ownership changes. All control variables are measured at the same quarter-end as the target price revisions.[15] They include: (i) change in EPS consensus (ΔEPS); (ii) change in recommendation consensus (ΔREC); (iii) past stock returns (*Mom*); (iv) change in the stock beta ($\Delta Beta$); (v) change in firm specific risk (ΔSD); (vi) change in return volatility (ΔVol); (vii) change in dividend yield (ΔDiv); (viii) price to earnings ratio (*PE*); (ix) book-to-market ratio (*BM*); (x) market capitalization (ln *Cap*); (xi) lagged institutional holding (L*inst*); (xii) return on equity (*ROE*); (xiii) change in the number of analysts following the firm in a quarter ($\Delta nStar$); (xiv) leverage (*Lev*), (xv) turnover (*Turn*), and (xvi) quarter (*Q*) and year (*Y*) dummies. Change in beta ($\Delta Beta$), change in standard deviation (ΔSD), and change in volatility (ΔVol) control for risk. Institutional ownership changes should be negatively correlated with risk because institutional investors prefer low volatility stocks. Company size (ln *Cap*) and change in deviation from consensus (ΔDiv) control for investment constraints. Change in number of stars following ($\Delta nStar$) and turnover (*Turn*) capture institutional investor preferences for visible companies and stock liquidity. Institutional ownership changes should be positively correlated with market capitalization, number of analysts following, and turnover but negatively correlated with dividends. Leverage (*Lev*) controls for capital structure. *PE* and *BM* capture institutional investor preferences for value–glamour trading. *ROE* controls for financial performance and *Mom* captures stock performance. Lagged institutional ownership (L*inst)* controls for initial investment positions. Quarter dummies control for seasonality in institutional ownership changes, as institutional investors tend to rebalance their portfolios and reallocate funds at the beginning of the year. Finally, *invMills* is the computed inverse Mills ratio for each observation in the sample from the duration model in equation (2). The measurement of control variables follows prior research.

To conduct the second analysis on the effect of target price quality on the likelihood of the occurrence of analyst star ranking events, I estimate a second duration model,

[14] Using the median instead of the mean does not affect the robustness of the results.
[15] Similar to previous research (e.g., O'Brien and Bhushan, 1990), I use changes in the endogenous variables rather than levels to eliminate any cross-sectional and temporal correlation unrelated to a causal relationship.

$$h_i\left(t \mid N(t), X\right) = h_0(t)\exp\left(\beta_1 TPerr + \beta_2 TPbold + \beta_3 EPSerr + \beta_4 RECret + \beta_5 LFR + \beta_6 Exp + \beta_7 Nfirm + \beta_8 Freq + \beta_9 StarBank + \beta_{10} inst\right) \quad (4)$$

where the dependent variable is the hazard rate of an *XSTAR* event occurring (that is, the likelihood of a star analyst losing star status at time *t*). As in equation (1), the term *N*(*t*) counts the number of times an event occurs before the end of the sample period. The term $h_0(t)$ is the baseline hazard, which is the rate of occurrence of the event of an analyst losing star status when all explanatory variables are equal to zero. The exponential term captures factors affecting the occurrence of the event. The covariates include variables capturing factors that are likely to determine the probability of an analyst losing a star ranking. The independent variables are similar to those in Leone and Wu (2007) and are measured in the year prior to the release of the *Institutional Investor* analyst ranking.[16] The covariates include the absolute target price forecast error (*TPerr*) and the absolute EPS forecast error (*EPSerr*). *TPbold* measures the boldness of the analyst target price forecast. *RECret* is the adjusted return based on the analyst recommendation. *LFR* is the analyst leader–follower ratio. The model controls for analyst experience (*Exp*), the number of firms the analyst is covering (*Nfirm*) and revision frequency (*Freq*). *StarBank* is a top bank indicator and *inst* is the level of institutional ownership in a firm. If analyst target price forecast error (*TPerr*) or boldness (*TPbold*) influences institutional decisions to vote analysts stars, there should be significant hazard ratios on those two covariates.

Table 2 reports descriptive statistics for all the variables in the study. Mean changes in beta, return volatility, firm-specific risk, and dividend yield are close to zero. Mean momentum is 0.02. The average change in EPS forecast revision is −0.01. The average of the two target price revisions by ranking status are 0.05 for both ΔTP_{star} and ΔTP_{non}. *PE* averages 2.34, *BM* 0.53, and *Lev* 0.23. The summary statistics for the other variables used in the second analysis show no particular concern for the duration analysis. Table 3 reports Pearson correlations between the dependent and independent variables in the two models. Although there are some

[16] The main difference is that Leone and Wu do not consider the target price forecast error (*TPerr*). I also control for the level of institutional ownership (*inst*). Leone and Wu (2007) use a probit analysis rather than a duration analysis to estimate the model. Estimation from a duration analysis is more robust because duration analysis focuses on the conditional probability of star ranking events persisting over time as a function of a set of explanatory variables, whereas a probit model links the unconditional probability of star ranking at any point in time to a set of explanatory factors, independently of past ranking events.

significant correlations between the independent variables, including the variables in the regressions does not create a multicollinearity problem.[17]

5. *Empirical results*

5.1. Univariate analysis

The underlying assumption behind my argument in the preceding discussion is that star analysts distinguish themselves with higher quality target prices. No prior evidence empirically documents whether reputable sell-side analysts produce higher-quality target price forecasts relative to non-reputable analysts. Thus, I use univariate analysis to validate this assumption. I test for differences in mean and median target price accuracy, EPS accuracy and target price boldness between the two groups of analysts and report the results in table 4. Consistent with expectations, star analysts make significantly smaller target price forecast errors and significantly smaller EPS forecast errors compared with non-star analysts. The results are significant according to both mean and median differences tests. However, I find that the degree of deviation from target price consensus is significantly smaller for star analysts than non-star analysts. This may suggest that star analysts face pressure to conform to the consensus when making target price revisions. I now examine whether institutional investors distinguish between the revisions of star and non-star analysts.

5.2. Star analysts and target price revisions

Before I estimate equation (2), I test the key assumption of the model, the proportionality of the hazard rates. Based on the Schoenfeld Residuals test and the time dependent covariates test, none of the covariates in the model violates the proportional hazard assumption.[18] Table 5 reports the coefficients and hazard ratios for the probability that star analysts make target price revisions for a firm in a quarter. The estimation spans the sample period 2000–2009. I estimate the Cox proportional hazard model where the event of interest is the disclosure of target price revisions by star analysts. The results show that star analysts are more likely to

[17] Adding the 47 industry and 10 year dummy variables and dummies for quarters 2 to 4 results in high multicollinearity between these variables. Therefore, the regression excludes the industry dummies. This does not change inferences.
[18] The time dependent covariates test includes interactions of the predictors and a function of the duration time in the model and tests for their significance. A significant interaction between any of the predictors and the duration time function indicates that the predictors are not proportional. The Schoenfeld Residuals test detects non-proportionality by testing for a non-zero slope from the regression of scaled Schoenfeld residuals on functions of time.

revise target prices for companies with larger numbers of shares outstanding, larger number of analysts following, larger institutional ownership level and larger number of institutional investors. Star analysts are also more likely to revise for companies with higher firm-specific risk. On the other hand, the coefficients of *Mom*, *PE*, and *Beta* are negative and significant indicating that star analysts are less likely to revise their target prices for companies with higher momentum, price to earnings ratio, and beta. I use the probabilities estimated from this model to compute the inverse Mills ratio for all observations in the sample and use this ratio in the second stage estimation to control for selection bias.

5.3. Target price revisions and changes in institutional ownership

I estimate the second stage of Heckman's regression using equation (3). The results in Table 6 show that there is a selection bias, indicated by the significant coefficients on *invMills*. Column 1 presents the estimation of the model using the entire sample and where the main independent variable of interest is ΔTP. This variable aggregates all target price revisions by star and non-star analysts. This estimation shows that target price revisions positively and significantly influence the change in institutional ownership with a coefficient of 0.439. This coefficient is significantly higher than the coefficients on the EPS revisions and recommendation changes, supporting previous findings in the literature that target prices contain information incremental to the information disseminated through other analyst forecasts. Table 6, column 2 decomposes the change in target price by analyst ranking. The coefficient on the first independent variable, ΔTP_{star}, captures the association between changes in institutional ownership and target price revisions by star analysts only. The coefficient on the second variable, ΔTP_{non}, captures institutional ownership changes association with target price revisions by non-star analysts. The results show institutional ownership change is positively related to the revisions of star analysts. In contrast, institutional ownership change is negatively related to the revisions of non-stars, with the results significant at 10%. This indicates that only star analyst target price revisions are informative to institutional investors. The observation that institutional investors change their ownership levels in the opposite direction of the target price revisions of non-star analysts may suggest that institutional investors do not trust the revisions of non-star analysts and consequently trade in the opposite direction of those revisions. The coefficients on the control variables that capture institutional preferences are generally consistent with the literature. Most coefficients are significant except for the coefficients on the change in dividend, leverage and the change in the number of analysts following. Change in institutional ownership is positively associated with price momentum, consistent with institutional investors having a higher preference for stocks with positive momentum. Change in institutional ownership is also positively associated with change in stock beta, change in standard deviation, PE ratio, and *ROE*. Also, the coefficient on turnover is positive, consistent with institutional investors preferring to trade liquid stocks. Institutional ownership change is negatively associated with initial institutional holdings. That is, the larger the institutional investors' holdings in a firm are at the beginning of a quarter, the less likely they will increase this holding during that quarter. I also find the coefficient on company size is significantly negative, suggesting that institutional investors trade small firms more actively.

To further understand the reaction of institutional investors to target price revisions by star and non-star analysts, I split the sample by the sign of the change in target price revision and report the results in table 7. I examine whether institutional investor behavior changes when analysts provide positive compared to negative target price revisions. I re-estimate equation (3) for two separate sub-samples of positive and negative changes in target price forecasts. Column 1 of table 7 presents the results for the sub-sample whether both groups of analysts provide upward target price revisions. This reduces the size of the sample to 9,019 observations. The results show that the change in institutional ownership is negatively related to the upward revisions of non-star analysts with the result being significant at 5%. Institutional ownership is not significantly related to the upward target price revisions by star analysts. The results imply that institutional investors do not fully trust the upward target price revisions of analysts generally. Column 2 presents the results for the sub-sample where both groups of analysts provide downward target price revisions. The results based on 7,921 observations suggest that institutional ownership changes are positively related to downward target price revisions by star analysts while the relationship is not significant for the downward revisions by non-star analysts. This last finding may be related to institutional investors finding negative target price revisions by star analysts more informative than their positive target price revisions. This supports findings by Clarke et al. (2012) on the association between institutional ownership changes and analyst recommendation upgrades and downgrades. The results are also consistent when I repeat the above analysis (untabulated) using the two other sub-samples when star analysts provide upward revisions while non-star analysts provide downward revisions or star analysts provide downward revisions and non-star analysts provide upward revisions.

5.4. Target price quality and analyst star ranking

The analysis of the effects of analyst ranking give useful insights into analyst and institutional behavior. The collective results suggest that analyst star ranking is a determinant of institutional investor reaction to analyst revisions. Now I examine whether analyst target price quality is also subject to market scrutiny. I conduct this analysis using a dynamic duration model. It is particularly important to use duration analysis for this estimation because duration analysis can examine the relationship between analyst transition from a star to a non-star state and the time spent in each state. It also examines the relationship between analyst transitions and other covariates determining the transition, such as analyst target price quality. Conducting this analysis using a static model, it would be impossible to address questions such as: Does the likelihood of going ex-star decrease with the length of time an analyst remains a star? And does the presence of low target price quality increase the risk of an analyst going ex-star?

Table 8 reports estimates of the duration model of equation (4). The table reports both coefficients and hazard ratios. The Cox regression model reports estimation for the likelihood of a star analyst losing star status (*XSTAR* event). The hazard rates give the relative rates of an event occurring. For example, in column 1, the table shows that the hazard rate on the star investment bank dummy is 0.681. This suggests that analysts who work for star rated banks face an ex-star rating hazard of 0.681 relative to the hazard of analysts who work for less popular brokers. That is, analysts of star banks have a lower incidence of ex-star rating than analysts of non-star banks. The hazard rate on *TPerr* is 1.369, significant at 1%, indicating that all else being equal, for every unit increase in target price error, the hazard of an analyst becoming ex-star changes by a factor of 1.369. In other words, there is a 36.9% increase in ex-star rating events for every one unit increase in target price error. The hazard rate on *TPbold* is 0.849, significant at 1%, suggesting that for every unit increase in target price deviation from the consensus, the hazard of an analyst becoming ex-star changes by a factor of 0.849. Consistently, the coefficient on *TPerr* is significantly positive while the coefficient on *TPbold* is significantly negative. This means that an increase in analyst target price error increases the rate of ex-star events occurring while an increase in analyst deviation from consensus decreases the hazard of ex-rating events. The main finding from this analysis is that the quality of target price revisions is crucial for analysts to maintain star status. This implies that the market penalizes high target price forecast errors when updating analyst reputations.

5.5. Sensitivity tests

The previous analysis shows that star analysts make target price revisions that are more credible than those of non-star analysts. Further, the study shows that the quality of analyst target prices affects analyst reputation. I test the robustness of the findings using a series of sensitivity tests. First, an alternative explanation for the main finding is that star analysts cover stocks that are easier to forecast or that are not covered by other analysts and that this may bias the results. To check the robustness of the results against this possibility, I conduct a univariate analysis and I find that star analysts cover stocks that are covered widely by non-star analysts. Additionally, I use an alternative research design by controlling for selection bias using matching procedures combined with a duration analysis. I match observations that have star analyst coverage with observations that have non-star analyst coverage while controlling for firm characteristics. The results for star analyst target prices (not tabulated) remain similar to the main analysis. Since this approach reduces the sample size, I do not use it in my main analysis.

Second, in the main analysis, I adopt the view that analyst target prices are public information, and it would be naïve for institutional investors to trade on past analyst target prices. Nonetheless, I test the sensitivity of the results to the inclusion of one-quarter lagged star and non-star analyst target price revisions. I find that the results are consistent with the main analysis and there are no significant coefficients on the lagged variables. The results of this robustness check also rules out the possibility that analysts make their target price revisions after observing the behavior of institutional investors. Moreover, I find that the results are consistent when I divide the sample into institutional holdings by active and passive institutional investors following Bushee (1998); active institutional investors find star revisions significantly more informative.

Additionally, I test the sensitivity of the main findings to controlling for additional variables that determine the analyst decision to make target price revision. I add four independent dummy variables to the duration model of equation (2) to control for seasoned equity offerings, convertible stocks, debt issues and merger and acquisition (M&A) transactions that take place within the duration of each observation in my sample. I also include a dummy variable that indicates whether the target price disclosure observation follows an earnings announcement by the company. I collect earnings announcements data from the CRSP/Compustat merged database. The equity and debt offerings, and M&A data are from

Thomson One Banker. I find that the results on the duration model as well as the results on the second stage analysis are not sensitive to this inclusion. I also test the sensitivity of the results to adding seven accounting indicators to equation (2): market to book ratio, earnings per share to price ratio, revenue to assets ratio, return on equity, dividend yield, leverage ratio, and a dummy variable to indicate whether the stock daily price exceeds the 200-day moving average. Those variables serve as additional control variables since companies with good financial and operating performance are more likely to receive greater analyst coverage. I find that the results are consistent with the main findings. Last, one of the main challenges in analyzing duration data is the presence of informative censoring. In my sample, informative censoring may occur if right-censored observations are likely to have higher or lower hazard rates than the rest of the sample, due to unobserved factors. Although this is very unlikely, I test the sensitivity of the results to dropping all right-censored observations. I also conduct a second test that expands the sample size by one year to cover a sufficient period to observe events for previously right-censored observations. Both results confirm that the main findings are not subject to informative censoring bias.

6. *Conclusion*

I present empirical evidence that analysts with star ranking draw significantly higher institutional interest. This result should give analysts a strong economic incentive to make informative target price revisions. I examine the information content of consensus target prices to institutional investors. The overall consensus forecast represents an aggregation of the opinions of all analysts following the firm. There are many reasons, however, why institutional investors could be sensitive to the information content of specific analyst target price revisions and not to the overall consensus. I therefore disaggregate the consensus by analyst ranking status in determining institutional investor preferences. Using a sample of I/B/E/S target price data between 2000 and 2009, I investigate the association between changes in institutional investment and analyst target price revisions by star analysts. I define a target price revision as informative if it is positively associated with changes in institutional ownership. The literature on changes in institutional ownership in response to changes in the analyst forecast consensus does not make it possible to understand which analysts issue informative target price revisions and why they do so. Such an understanding is critical to assessing the role of analysts in information production and in influencing institutional investors' decisions. My study presents the first attempt to analyze whether analyst target prices are aimed at exploiting unsophisticated investors.

My evidence shows that aggregating all target prices into a consensus forecast leads to an incomplete assessment of the value of the information content of analyst target prices. I show that star analysts have different influences on institutional investor decisions. The results indicate that only star analysts' target prices are informative to institutional investors and there is a sizeable portion of analysts whose target price revisions have no noticeable impact on institutional trading behavior. I also show that non-star analysts are less likely to attract institutional investor attention through their target price revisions. My analysis shows that equity analysts can add value by offering more information, through their target prices, than is already available to the public. They can shape market perceptions and expectations and are in effect key protagonists in influencing market reaction.

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Table 1
Variable definitions

Variable symbol	Name	Definition
Beta	Beta	The coefficient in a regression of monthly returns of firm *i* on CRSP value-weighted index returns over the 36 months prior to the end of quarter *t*.
Δ*Beta*	Change in beta	The change in the value of *Beta* for the stock between quarter *t* and quarter *t* −1.
BM	Book to market ratio	The total book value of the firm at the end of the previous fiscal quarter divided by total market equity on the last trading day of the previous quarter.
Δ*Div*	Change in dividend yield	The change in dividend per share for quarter *t* from Compustat divided by the share price at the end of the quarter.
Δ*EPS*	Change in EPS consensus	The latest consensus EPS forecast in quarter *t*, minus the latest consensus EPS forecast in quarter *t*−1, divided by the stock price at the end of quarter *t*−1, winsorized at the upper and lower 1% levels (using the summary file).
Δ*inst*	Change in institutional ownership	The difference in percentage ownership of institutional investors between quarter *t* and quarter *t*−1. Percentage ownership is shares held by institutional investors divided by total shares outstanding at the end of the same quarter, winsorized at the upper and lower 10% levels.
Lev	Leverage	Total debt divided by the market value of assets at the end of quarter *t*.
L*inst*	Lagged institutional ownership	Institutional ownership as a percentage of shares outstanding at the end of quarter *t*−1 from 13F.
ln *Cap*	Market capitalization	Natural log of stock price multiplied by the number of shares outstanding at the end of quarter *t*.
L*nStar*	Lagged number of star analysts following	Natural log of the total number of star analysts following the stock of firm *i* in quarter *t* −1.
ln *Shrs*	Number of shares outstanding	Natural log of the total number of shares outstanding for firm *i* at the beginning of quarter *t*.
Mom	Momentum	Stock abnormal return for the three months prior to quarter *t*.
Δ*nAnlys*	Change in number of analysts following	The change in the natural log of the total number of analysts covering the stock of firm *i* between quarter *t* and quarter *t*−1.
Neg	Negative returns	Takes the value 1 if *Mom* is negative, and zero otherwise.
PE	Price earnings ratio	Stock price divided by the sum of income before extraordinary items in the firm's most recent fiscal quarters from Compustat, winsorized at the upper and lower 1% levels.
Δ*REC*	Change in recommendation consensus	The difference between the consensus recommendations of quarter *t* and quarter *t*−1, scaled by the consensus recommendation during quarter *t*−1. Recommendations from I/B/E/S are recoded so that 5 represents a strong buy, 4 represents a buy, and 3, 2, and 1 represent hold, sell, and strong sell.

(**Continued**)

Table 1 (**Continued**)

Variable symbol	Name	Definition
ROE	Return on equity	Quarterly net income divided by common equity of the previous quarter from Compustat, winsorized at the upper and lower 1% levels.
SD	Standard deviation	The standard deviation of the residuals in a regression of monthly returns of firm *i* on CRSP value-weighted index returns over the 36 months prior to the end of quarter *t*.
ΔSD	Change in standard deviation	The change in the value of *SD* between quarter *t* and quarter $t-1$.
Top	Number of large institutional investors	Natural log of one plus the aggregate number of large institutional investors holding shares in firm *i* in quarter *t*. Large institutional investors are defined as the top 100 institutional investors in terms of their total holdings in all firms in the market.
ΔTP	Change in TP consensus	The difference between the consensus target prices of quarter *t* and quarter $t-1$, divided by the consensus target price of quarter $t-1$.
ΔTP_{non}	Change in non-star TP consensus	The difference between the consensus non-star target prices of quarter *t* and quarter $t-1$, divided by the consensus non-stars target price of quarter $t-1$.
ΔTP_{star}	Change in star TP consensus	The difference between the consensus star target prices of quarter *t* and quarter $t-1$, divided by the consensus stars target price of quarter $t-1$.
Turn	Turnover	Natural log of the average trading volume in the quarter, divided by the number of shares outstanding at the end of the quarter.
ΔVol	Change in volatility	The change in the standard deviation of firm *i*'s daily return in quarter *t*.
EPSerr	EPS forecast error	The absolute value of the difference between the analyst EPS forecast and the actual EPS at the end of the forecast period scaled by the current share price.
Exp	Analyst experience	Total number of years since the analyst started reporting forecasts to I/B/E/S.
Freq	Forecast frequency	The total number of times the analyst revises their forecast in a year.
inst	Institutional ownership	The total level of institutional ownership in a firm in the most recent quarter.
LFR	Leader follower ratio	The leader–follower ratio from Cooper et al. (2001), equal to the ratio of the number of days the analyst is a follower to the number of days the analyst forecast is a leader.
Nfirm	Firms following	The number of firms the analyst is following in a year.
RECret	Recommendation return	The difference between the buy-and-hold returns of the recommended stock and the value weighted CRSP index from the day before the analyst recommendation date to 30 days after the recommendation date, taking a long position for Strong Buy and Buy recommendations and a short position for Hold, Sell and Underperform recommendations.

(**Continued**)

Table 1 (Continued)

Variable Symbol	Name	Definition
StarBank	Star bank dummy	Takes the value 1 if the brokerage firm for which the analyst works is *Institutional Investor* top bank, and zero otherwise.
TPbold	Target price forecast boldness	The absolute value of the difference between the analyst TP forecast and the current TP consensus forecast scaled by the current share price.
TPerr	Target price forecast error	The absolute value of the difference between the analyst TP forecast and the actual price of the share in the market at the end of the forecast period scaled by the current share price.
STAR	Star dummy	Takes the value 1 if a non-star analyst is rated a star for the first time in year *t*, and zero otherwise.
XSTAR	Ex-star dummy	Takes the value 1 if either a star analyst is ex-rated in year *t*, and zero otherwise.

Table 2
Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	25th	Median	75th	Max
Beta	52483	1.22	0.95	−2.44	0.57	1.05	1.67	9.89
Δ*Beta*	52483	0.01	0.32	−5.64	−0.12	0.01	0.13	4.31
BM	52483	0.53	0.65	−76.85	0.27	0.44	0.66	17.42
Δ*Div*	52483	0.00	0.02	−1.16	0.00	0.00	0.00	1.16
Δ*EPS*	52483	−0.01	0.64	−3.51	−0.07	0.01	0.09	3.18
Δ*inst*	52483	0.54	3.63	−5.54	−1.71	0.25	2.77	7.10
Lev	52483	0.23	0.22	0.00	0.04	0.20	0.36	6.70
L*inst*	52483	0.65	0.25	0.00	0.49	0.69	0.84	1.00
ln *Cap*	52483	7.30	1.67	0.58	6.11	7.18	8.36	13.31
L*nStar*	52483	0.74	1.10	0.00	0.00	0.00	1.00	8.00
ln Shrs	52483	11.04	1.28	6.31	10.16	10.88	11.78	18.30
Mom	52483	0.02	0.24	−0.91	−0.10	0.01	0.12	10.84
Δ*nAnlys*	52483	0.27	0.93	−0.92	−0.27	0.00	0.50	19.00
Neg	52483	0.49	0.50	0.00	0.00	0.00	1.00	1.00
Neg ×*Mom*	52483	-0.07	0.11	-0.91	-0.10	0.00	0.00	0.00
PE	52483	2.34	7.61	−24.93	0.13	0.93	3.18	46.69
Δ*REC*	52483	−0.03	0.20	−1.00	−0.06	0.00	0.00	4.00
ROE	52483	0.02	0.11	−0.66	0.01	0.03	0.05	0.43
SD	52483	0.47	0.28	0.09	0.28	0.40	0.59	6.29
Δ*SD*	52483	−0.01	0.08	−3.88	−0.02	0.00	0.02	1.97
Top	52483	2.21	1.77	0.00	0.00	3.18	3.76	4.51
Δ*TP*	52483	0.05	0.39	−0.69	−0.15	0.00	0.16	2.00
Δ*TPnon*	52325	0.05	0.39	−0.69	−0.16	0.00	0.17	2.01
Δ*TPstar*	21551	0.05	0.37	−0.73	−0.15	0.01	0.17	1.82
Turn	52483	1.99	0.86	−2.65	1.46	2.03	2.56	5.82
Δ*Vol*	52483	0.00	0.01	−0.66	−0.01	0.00	0.00	0.66
EPSerr	340197	0.03	0.20	0.00	0.00	0.00	0.01	12.78
Exp	340197	4.73	2.87	0.00	2.00	5.00	7.00	10.00
Freq	340197	1.23	0.62	0.00	0.69	1.39	1.61	3.09
STAR	340197	0.04	0.19	0.00	0.00	0.00	0.00	1.00
inst	340197	0.64	0.26	0.00	0.49	0.70	0.84	1.00
LFR	340197	0.93	0.99	0.00	0.21	0.64	1.30	7.31
Nfirms	340197	2.51	0.66	0.00	2.20	2.64	2.89	4.63
RECret	340197	0.01	4.13	−1278	−0.07	0.01	0.09	1200
StarBank	340197	0.31	0.46	0.00	0.00	0.00	1.00	1.00
TPbold	340197	0.33	0.57	0.00	0.08	0.18	0.36	16.44
TPerr	340197	0.42	0.52	0.00	0.14	0.31	0.52	15.29
XSTAR	340197	0.08	0.26	0.00	0.00	0.00	0.00	1.00

Notes: The table reports descriptive statistics for the sample of institutional ownership observations for US stocks, 2000–2009. Table 1 gives variables definitions.

Table 3
Pearson correlations

	Beta	Δ*Beta*	*BM*	Δ*Div*	Δ*EPS*	Δ*inst*	*Lev*	L*inst*	ln *Cap*
Δ*Beta*	0.150*								
BM	0.013*	0.053*							
Δ*Div*	−0.002	−0.007	−0.035*						
Δ*EPS*	−0.026*	−0.012*	−0.037*	−0.004					
Δ*inst*	0.014*	0.017*	−0.044*	−0.008	0.032*				
Lev	−0.077*	0.028*	−0.010*	0.003	−0.005	0.000			
L*inst*	0.067*	−0.017*	−0.045*	0.006	0.007	−0.148*	0.034*		
ln *Cap*	−0.158*	−0.013*	−0.220*	0.011*	0.052*	−0.007	0.081*	0.170*	
L*nStar*	−0.066*	0.013*	−0.065*	0.003	0.016*	−0.020*	0.083*	0.185*	0.507*
ln *Shrs*	0.006	−0.006	−0.100*	0.001	0.011*	−0.025*	0.089*	0.118*	0.823*
Mom	0.035*	0.037*	0.101*	−0.028*	0.057*	0.148*	0.018*	−0.048*	−0.075*
ΔnAnlys	−0.005	0.011*	−0.028*	0.008	0.006	0.014*	0.011*	0.009	0.021*
Neg	0.038*	0.014*	−0.031*	0.015*	−0.064*	−0.114*	−0.019*	0.013*	0.002
Neg ×*Mom*	−0.144*	−0.033*	−0.013*	−0.025*	0.085*	0.175*	0.017*	−0.006	0.114*
PE	−0.033*	0.001	0.040*	−0.002	0.008	0.002	−0.066*	−0.038*	−0.182*
ΔREC	0.005	0.002	0.000	0.001	0.010*	0.011*	−0.002	−0.0184*	−0.019*
ROE	−0.133*	−0.013*	−0.154*	0.002	0.046*	0.039*	0.017*	0.027*	0.194*
SD	0.563*	−0.020*	−0.051*	−0.002	−0.011*	0.045*	−0.089*	−0.024*	−0.353*
Δ*SD*	0.021*	0.184*	0.013*	−0.019*	0.009*	0.095*	0.027*	−0.038*	0.024*
Top	0.000	0.035*	−0.036*	0.000	0.001	−0.011*	−0.033*	0.058*	0.129*
Δ*TP*	0.016*	−0.041*	−0.124*	0.004	0.075*	0.101*	−0.005	−0.012*	0.052*
Δ*TPnon*	0.017*	−0.040*	−0.123*	0.005	0.074*	0.098*	−0.005	−0.010*	0.053*
Δ*TPstar*	−0.006	−0.067*	−0.139*	−0.006	0.070*	0.063*	−0.009	0.006	0.049*
Turn	0.385*	0.008	−0.046*	0.010*	−0.008	0.010*	0.010*	0.455*	0.150*
Δ*Vol*	−0.030*	0.026*	−0.047*	0.044*	−0.015*	−0.092*	0.010*	0.023*	0.017*

(Continued)

Table 3 (Continued)

	L*nStar*	ln *Shrs*	*Mom*	Δ*nAnlys*	*Neg*	*Neg* ×*Mom*	*PE*	Δ*REC*	*ROE*	*SD*	Δ*SD*	*Top*	Δ*TP*	Δ*TPnon*	Δ*TPstar*	*Turn*
ln *Shrs*	0.481*															
Mom	−0.014*	−0.016*														
Δ*nAnlys*	−0.156*	0.013*	0.014*													
Neg	−0.009*	−0.001	−0.642*	−0.025*												
Neg ×*Mom*	0.060*	0.053*	0.676*	−0.024*	−0.627*											
PE	−0.102*	−0.228*	−0.009*	−0.012*	0.009*	−0.008										
Δ*REC*	−0.006	−0.020*	0.028*	−0.051*	−0.027*	0.021*	0.008									
ROE	0.070*	0.052*	0.068*	0.010*	−0.064*	0.177*	0.015*	−0.002								
SD	−0.198*	−0.195*	0.020*	−0.001	0.040*	−0.188*	−0.005	0.010*	−0.160*							
Δ*SD*	0.007	0.008	0.095*	−0.004	−0.034*	0.034*	0.009*	−0.004	0.049*	0.080*						
Top	0.096*	0.144*	0.020*	0.025*	−0.017*	0.021*	−0.031*	−0.013*	0.011*	−0.106*	0.044*					
Δ*TP*	−0.017*	−0.019*	0.121*	0.085*	−0.106*	0.144*	0.003	0.135*	0.079*	0.083*	0.071*	−0.057*				
Δ*TPnon*	−0.015*	−0.017*	0.121*	0.080*	−0.107*	0.144*	0.004	0.130*	0.079*	0.083*	0.079*	−0.057*	0.970*			
Δ*TPstar*	−0.027*	−0.034*	0.136*	0.038*	−0.123*	0.176*	0.009	0.083*	0.092*	0.074*	0.083*	−0.069*	0.770*	0.683*		
Turn	0.133*	0.148*	0.010*	0.040*	0.033*	−0.175*	−0.075*	−0.012*	−0.042*	0.312*	−0.013*	0.047*	0.037*	0.035*	−0.019*	
Δ*Vol*	0.006	−0.014*	−0.113*	0.068*	0.077*	−0.207*	0.003	0.002	−0.062*	−0.009	−0.235*	−0.048*	−0.047*	−0.048	−0.080*	0.063*

Notes: The table reports Pearson correlations between the variables. Table 1 gives variables definitions.
* indicates significance at the 5% level

Table 4
Univariate analysis: Star and non-star analysts

	Star analysts		Non-star analysts		Mean difference		Median difference	
	Mean	Median	Mean	Median	*t*-stat	*p*-value	*z*-stat	*p*-value
TPerr	0.387	0.286	0.424	0.311	14.77	0.000	19.57	0.000
EPSerr	0.027	0.003	0.033	0.005	6.78	0.000	30.94	0.000
TPbold	0.294	0.152	0.337	0.181	16.21	0.000	28.84	0.000

Notes: The table reports the mean and median values of analyst target price error, EPS error and target price boldness for star and non-star analyst groups. The table also reports mean and median differences tests for the three variables between the two groups. Table 1 gives variables definitions.

Table 5
Star analysts target price revisions: Cox's proportional hazard model

	Coefficient	Hazard rates
ln *Shrs*	0.206***	1.229***
	[0.000]	[0.000]
Mom	−0.340***	0.711***
	[0.000]	[0.000]
Neg	−0.115***	0.892***
	[0.000]	[0.000]
Neg ×*Mom*	0.798***	2.221***
	[0.000]	[0.000]
PE	−0.010***	0.990***
	[0.000]	[0.000]
Beta	−0.212***	0.809***
	[0.000]	[0.000]
SD	0.324***	1.383***
	[0.000]	[0.000]
Top	0.096***	1.100***
	[0.000]	[0.000]
L*inst*	0.151**	1.163**
	[0.021]	[0.021]
L*nStar*	0.304***	1.356***
	[0.000]	[0.000]
Industry dummy	Yes	
Wald χ^2	2901.93	
Prob > χ^2	0.000	
N	52,483	

Notes: The table reports estimates of a duration model of the determinants of star analyst decisions to revise target prices in a particular quarter. The table reports the coefficients and the hazard ratios. The estimation is based on 52,483 observations of which 21,551 observations are uncensored. Standard errors are adjusted for intra-group correlation among stocks. Variables definitions are in table 1.
* p<0.1, ** p<0.05, *** p<0.01.

Table 6
Institutional ownership changes and target price revisions: Correcting for selection bias

$\Delta inst$	(1)	(2)
ΔTP	0.439***	
	[0.000]	
ΔTP_{star}		0.272***
		[0.003]
ΔTP_{non}		−0.172*
		[0.066]
ΔEPS	0.072***	0.095**
	[0.008]	[0.048]
ΔREC	0.023	0.507**
	[0.765]	[0.037]
Mom	1.924***	2.170***
	[0.000]	[0.000]
L*inst*	−2.855***	−3.595***
	[0.000]	[0.000]
BM	−0.203**	−0.316***
	[0.038]	[0.000]
$\Delta Beta$	0.112**	0.236**
	[0.042]	[0.015]
ΔDiv	−0.244	−0.534
	[0.816]	[0.762]
ΔSD	0.874***	1.080**
	[0.000]	[0.031]
ΔVol	−11.973***	−10.564***
	[0.000]	[0.000]
Lev	−0.013	−0.024
	[0.872]	[0.835]
ln *Cap*	−0.077***	−0.132***
	[0.000]	[0.000]
PE	0.010***	−0.001
	[0.000]	[0.772]
ROE	0.460**	−0.126
	[0.013]	[0.632]
Turn	0.476***	0.501***
	[0.000]	[0.000]
$\Delta nAnlys$	0.017	0.032
	[0.324]	[0.187]
invMills	−3.904***	−5.501***
	[0.000]	[0.000]
Constant	2.424***	3.413***
	[0.000]	[0.000]
Year dummy	Yes	Yes
Quarter dummy	Yes	Yes
R-squared	9.60%	9.60%
N	52,483	21,551

Notes: The table provides estimates of the relation between institutional ownership changes and analyst target price revisions. The dependent variable in all regressions is the change in institutional ownership, $\Delta inst$. The first column aggregates all analyst target price revisions and uses the variable ΔTP while the second column aggregates the change in target prices by analyst group: Star analysts' revisions, ΔTP_{star}, and non-star analysts' revisions, ΔTP_{non}. The regressions correct for selection bias by including the inverse Mills ratio computed using the estimated probabilities for each observation from the duration model in table 5. Standard errors are adjusted for clustering at the firm level to correct for cross-sectional dependence. Table 1 gives variables definitions.
* p<0.1, ** p<0.05, *** p<0.01.

Table 7
Institutional ownership changes and positive and negative target price revisions

$\Delta inst$	(1) Positive target price revisions	(2) Negative target price revisions
ΔTP_{star}	−0.031	0.653*
	[0.818]	[0.050]
ΔTP_{non}	−0.362**	0.365
	[0.011]	[0.302]
ΔEPS	0.023	−0.001
	[0.777]	[0.990]
ΔREC	0.414	0.524
	[0.300]	[0.160]
Mom	1.586***	2.411***
	[0.000]	[0.000]
L*inst*	−4.473***	−2.906***
	[0.000]	[0.000]
BM	0.017	−0.208**
	[0.914]	[0.019]
$\Delta Beta$	0.489***	0.327**
	[0.002]	[0.020]
ΔDiv	−5.048***	−0.347
	[0.009]	[0.813]
ΔSD	1.624*	0.944
	[0.062]	[0.200]
ΔVol	−8.476*	−6.879**
	[0.099]	[0.031]
Lev	0.112	−0.084
	[0.529]	[0.658]
ln *Cap*	−0.236***	−0.045
	[0.000]	[0.190]
PE	0.005	−0.012
	[0.457]	[0.138]
ROE	−0.667	0.18
	[0.148]	[0.629]
Turn	0.602***	0.476***
	[0.000]	[0.000]
$\Delta nAnlys$	0.003	0.01
	[0.794]	[0.402]
invMills	−5.602***	−6.503***
	[0.005]	[0.002]
Constant	5.490***	2.244***
	[0.000]	[0.000]
Year dummy		
Quarter dummy		
R-squared	10.7%	12.3%
N	9,019	7,921

Notes: The table reports estimates of the relationship between positive and negative target price revisions and institutional ownership changes. The dependent variable is the change in institutional ownership. In the first column the regression results are based on the sub-sample where both target price revisions by star and non-star analysts are positive. The second column presents the results for the sub-sample where both target price revisions by star and non-star analysts are negative. The regression corrects for selection bias by including the inverse Mills ratio computed using the estimated probabilities for each observation from the duration model in table 5. Standard errors are adjusted for clustering at the firm level to correct for cross-sectional dependence. Table 1 gives variables definitions.
* p<0.1, ** p<0.05, *** p<0.01.

Table 8
Duration analysis of the likelihood of analysts losing star status

	XSTAR	
	Coef.	Hazard rates
TPerr	0.314***	1.369***
	[0.000]	[0.000]
EPSerr	−0.713***	0.490***
	[0.000]	[0.000]
Tpbold	−0.164***	0.849***
	[0.001]	[0.001]
RECret	−0.002**	0.998**
	[0.016]	[0.016]
LFR	0.057***	1.059***
	[0.000]	[0.000]
Exp	−0.135***	0.873***
	[0.000]	[0.000]
Nfirms	0.075	1.078
	[0.454]	[0.454]
Freq	−0.173***	0.842***
	[0.000]	[0.000]
StarBank	−0.384***	0.681***
	[0.000]	[0.000]
inst	−0.157	0.854
	[0.166]	[0.166]
Wald χ^2	228.16	
Prob $> \chi^2$	0.000	
N	90,702	

Notes: This table reports estimates of a duration model of the determinants of analysts star rating events. *XSTAR* is an event of a star analyst losing their star ranking. The table estimates the duration model for the likelihood of an *XSTAR* event. The table reports both coefficients and the hazard ratios. Variables definitions are provided in table 1.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$.