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To the Graduate Council:

I am submitting herewith a dissertation written by Haosi Chen entitled "Two Essays on Sell Side Equity Analysts." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

Andrew T. Puckett, Major Professor

We have read this dissertation and recommend its acceptance:

James A. Chyz, Eric K. Kelley, David A. Masler

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Two Essays on Sell Side Equity Analysts

A Dissertation Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Haosi Chen
May 2018

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ABSTRACT

This dissertation examines the role of sell side equity analysts in the capital market. The first chapter examines whether sell side analysts, who as an important information intermediary, process information that has been shown to predict future stock returns by academic studies. Our sample includes seven firm level characteristics (e.g., anomalies) that have robust return predictability. We test whether analysts' consensus recommendation and expected returns are consistent with the trading strategies these anomaly variables prescribe. We do not find evidence that sell side analysts are persistently incorporating such information in the correct way. Instead, analysts from certain brokerage firms persistently issue target prices in the opposite direction as what anomaly variables suggests. Our findings suggest that analysts are likely subject to biased expectations and could improve their research quality by incorporating anomaly characteristics. The second chapter investigates whether institutional investors value sell side analysts' qualities differently. We fill the gap in the literature with a novel hand collected dataset, which shows the best sell side analysts voted by hedge funds and institutional investors, respectively. Examining the research output of investors' revealed preferences allows us to detect the qualities valued by these investors. We find that hedge funds preferred analysts update research more frequently and issue less optimistic stock recommendations. The recommendations revised by these analysts also receive stronger market response in the subsequent six months than those made by other "All-Star" sell side analysts. These findings suggest that there are cross sectional differences among sell side analysts that are associated with clients' needs.

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INTRODUCTION

Sell side analysts are important information intermediary in the capital markets. The information they collect from firms and communicate with investors is important for market efficiency. Both practitioners and academics are interested in the role analysts play in the market. Earlier studies investigate whether analysts provide value adding information by examining analysts' ability to forecast earnings and pick stocks (Womack (1996)). Due to the unobservable nature of analysts' research process, there is a gap in the literature concerning what information is used by sell side analysts. Recently studies are able to examine the question by collecting information on analyst characteristics (e.g., sell side analysts' school ties (Cohen, Frazzini and Malloy (2010)), analysts' prior industry working experience (Bradley et al. (2017)). The first chapter of this dissertation examines the information used by analysts in their research process. Specifically, we look into a group of variables (e.g., anomalies) that are shown to robustly predict future stock return by academic research. Papers have shown that a long short trading strategy based on anomaly variables generates significant risk-adjusted returns. By examining whether analysts issue recommendations (or target prices) in the consistent way as those trading strategies suggests, we infer whether analysts are incorporating these return predicting variables in their research process

The second chapter of this dissertation investigates whether institutional investors value sell side analysts' qualities differently. Institutional investors are a prominent group of market participants due to their high ownership of equity in the stock market. The interaction between institutional investors and sell side analysts is not fully explored by prior literature potentially due to unavailable data. Using a hand collected dataset, we observe the revealed preferences of sell side analysts by a distinct group of institutional investors, hedge funds. Hedge funds are distinctly different from other long-only asset managers due to their investment strategies and instruments. By comparing the research outputs of the best sell side analysts voted by hedge funds and institutional investors, respectively, we infer the cross sectional differences among "All-star" sell side analysts potentially associated with their clients' need.

CHAPTER I
DO SELL SIDE EQUITY ANALYSTS PAY ATTENTION TO ACADEMIC RESEARCH?

The first chapter is co-authored with Dr. Andy Puckett.

Abstract

We contribute to the debate surrounding sell-side analyst skill in a novel way. In particular, we investigate whether analysts' incorporate salient firm-level information in their recommendations or target prices that has been shown by the academic literature to predict future abnormal performance (i.e., anomalies). In aggregate, there is little relation between analysts' recommendation levels and anomaly prescriptions, however, analysts' target price estimates are significantly higher for stocks in the "short" leg of an anomaly when compared to stocks in the "long" leg. In the cross section, we do not find evidence that certain brokerage firms or "All-star" analysts are anomaly savvy. However, evidence suggests that analyst's experience tends to mitigate such bias. We conjecture that the value of analysts' research would be significantly enhanced if analysts paid attention to academic research.

1. Introduction

Sell-side analysts are important intermediaries whom market participants rely on to gain information and insights about firms or industries. For investors, analysts' ability to detect mispriced stocks and predict abnormal future returns is crucial. Thus, one should expect savvy analysts to incorporate information (particularly salient information) that predicts future abnormal performance into their research reports. For decades, academic literature has documented trading strategies based on firm-level characteristics that generate economically large abnormal returns. While academics often debate whether the documented abnormal performance reflects true mispricing or latent risk factor exposure (McLean and Pontiff, 2016), the fact that these firm characteristics are correlated with realized future return provides useful information for stock picking. While the majority of existing Finance literature focuses on finding new anomalies or whether anomaly returns are robust, a new and growing literature asks how certain market participants react to existing anomalies[1]. This paper examines whether sell-side analysts incorporate academic research (specifically anomalies) into their research reports and whether certain analyst characteristics, e.g., all-star designation, analyst's tenure and analysts who enjoy access to shared research resources at their brokerage firms are more likely to be academically sophisticated.

Our research experiment adds to several areas of the existing academic literature. Of central importance is our contribution to the literature investigating sell-side analysts' skill and whether analysts provide new (material and value relevant) information to equity market participants. While researchers have historically evaluated the value of analysts' research by examining the abnormal returns around stock recommendations (e.g., Womack (1996)), such inference could be spurious when analysts' research issuances are systematically correlated with corporate events (Bradley, et al. (2014); Altınkılıç, Hansen (2009)). Instead of using an event study to infer information in analysts' research, we evaluate analysts' skill by examining the relation between analysts' stock recommendations (and price target estimates) and stock anomaly characteristics. Our evaluation occurs over longer horizons and allows us to test hypotheses related to skill in sell-side analyst research while being divorced from issues of confounding events (see Bradley, Clarke, Lee and Ornthanalai, 2014).

We find that sell-side analysts' consensus recommendations (and recommendation revisions) are positively associated with anomaly prescriptions. While the association is statistically significant, the magnitudes are questionable from an economic perspective. In contrast, analysts' target price estimates are too high for stocks in the short leg of anomalies and too low for stocks in the long leg of anomalies. Overall, while analysts do not seem to systematically incorporate anomaly prescriptions in their recommendations or target prices, it is possible that some segments of the analyst population are academically sophisticated. We investigate whether analysts at particular brokerage firms, analysts with more experience or institutional

[1] Edelen, Ince and Kadlec (2016) show that institutional investors in aggregate trade contrary to anomaly prescriptions. Wu and Zhang (2015) show that short sellers use anomaly based strategies to short overpriced firms and avoid underpriced firms.

investor all-star analysts incorporate anomaly information in their research reports. Interestingly, we find that some brokerage firms persistently issue target prices that are negatively correlated with anomaly prescriptions – we term these brokerages "academically unsophisticated." A long-short trading strategy that buys stocks favored by academically unsophisticated brokerage firms and shorts stocks not favored by these brokerages generates negative abnormal returns of approximately 49 basis points per month. We also show that this perverse behavior is not mitigated in the subsample of all-star analysts.

We begin our examination using a methodology employed in Edelen et al. (2016) to construct an aggregate measure for seven prominent anomalies found in the academic literature. The set of anomalies includes *net operating assets* (NOA), *gross profitability* (GP), *investment-to-assets* (IVA), *Ohlson Score* (O-score), *book-to-market* (BM), *undervalued minus overvalued* (UMO) and *momentum*. These variables have been found to predict significant future abnormal returns (Hirshleifer, et al. (2004), Lyandres, et al. (2007), Novy-Marx (2013), Dichev (1998), Fama and French (1992), Hirshleifer and Jiang (2010), Jegadeesh and Titman (1993)). For five of the seven anomalies (excluding momentum and UMO), we do the following: in June of each calendar year (t) we sort stocks into quintile portfolios based on anomaly characteristics obtained from accounting information at the end of year t-1. We assign each quintile a value between -2 and +2, where -2 (+2) is assigned to the quintile portfolio that anomaly prescriptions suggest investors should take a short (long) position. For undervalued minus overvalued (UMO), in June of each calendar year (t) we sort stocks into long, short and neutral portfolios based on firms' financing during fiscal year t-1 and t-2. We assign value 2, 0, and -2 to the long, short and neutral portfolios respectively. For momentum, we amend this methodology slightly by updating quintile portfolio sorts each quarter (rather than in June of each year) based on stocks' prior 12 month returns. We then calculate an aggregate "anomaly score" for each stock in each quarter by summing the portfolio assignments across all anomalies that we consider. We show that these ranks are informative for future abnormal returns as the value-weighted (equal-weighted) difference in performance between extreme quintiles is 2.49% (3.12 %) per quarter.

We then gather sell-side analysts' recommendations and target prices from I/B/E/S for firms where we have anomaly data. We examine two measures related to analysts' recommendations: the consensus recommendation and its changes over a long horizon (six quarters). The consensus recommendation is the average of the most recent recommendations by all analysts over the prior 12 months. We take the difference in the consensus recommendations over the prior six quarters as the change in recommendation. The long horizon covers the time period when stocks take on anomaly characteristics and gives analysts sufficient time to access relevant information.

We also examine analysts' implied/expected return from their target price estimates. Target prices have been found to include additional information beyond recommendations and earnings forecasts. Its continuous nature gives a more granular measure of analysts' opinions of the stock returns. We scale the target price by the prior day stock price to get the implied (expected) return measure. The consensus implied return each quarter is the average of the most recent implied returns by all analysts over the prior 12 months.

We examine the association between analysts' recommendations (and implied returns) and stocks' aggregate anomaly score after controlling for variables that have been found to be correlated with stock recommendations (and implied expected returns). We show that as the stock moves from the sell group (bottom quintile of anomaly score) to buy group (top quintile of anomaly score), its consensus recommendation increases by 0.04, which is economically small compared with a standard deviation of 0.56. Alternatively, analysts' implied returns are negatively associated with stocks' anomaly characteristics. As stocks move from the sell (bottom quintile anomaly rank) to the buy (top quintile anomaly rank), the consensus implied return decreases by 5.2%, which is about 30.99% of the standard deviation. Such result suggests that analysts, in aggregate, consider the stock is overpriced when it's in fact undervalued according to anomaly prescriptions.

The above findings on analysts' recommendations and target prices suggest analysts consider anomaly characteristics differently when they issue recommendations and target price estimates. Three potential reasons could explain the seemingly inconsistent findings. Firstly, recommendation values are discrete and bounded, its high skewness towards buy recommendations might not allow the tests to pick up all the details. Second, recommendations and target prices could contain different information. For example, Brav and Lehavy (2003) find that analysts' target prices provide additional information controlling for information in their recommendations and earnings forecasts. Huang, Mian, Sankaraguruswamy (2009) show that a trading strategy that combines analysts' recommendations and target prices together outperforms a strategy that only adopts one analyst output. Third, analysts might strategically distort information communicated through different research outputs. Malmendier and Shanthikumar (2014) show that affiliated analysts and a large group of unaffiliated analysts have incentives to "speak in two tongues", issuing overoptimistic recommendations but more beatable earnings forecasts for covered firms.

If the regression coefficients from the multivariate regression is true concerning analysts' skill at processing anomaly variables to recommend stocks, we would expect that there are analysts in the cross section who persistently do so. As analysts' skill and incentives are plausibly different in the cross section, ideally we would investigate the heterogeneity in processing anomalies at the analyst level. However, on average, an individual analyst covers a small number of stocks and issues about two recommendations and target prices each year for each covered stock. Because of these limitations in statistical power, we examine potential skill heterogeneity at the brokerage firm level. Research has suggested shared value-adding information among fund managers within the same fund management complex (Pomorski (2009)), between research and asset management departments in a full service brokerage firm (Irvine, Simko and Nathan (2004)) and among analysts who have access to in-house macroeconomists (Hugon, Kumar, and Lin (2015)) and Washington policy analysts (Bradley, Gokkaya, Liu and Michaely (2017)). We conjecture that some sell-side analysts would have access to shared information within the affiliated brokerage firm. If such shared information is related to anomaly characteristics and impacts analysts' research outputs, we expect to pick up such characteristic through systematic variation at the brokerage firm level.

We first identify whether the recommendation (or implied return) from a particular brokerage firm is consistent with anomaly prescriptions. We run cross-sectional regressions each quarter and include an interaction term between a brokerage firm fixed effect and the stock's aggregate score rank. We interpret the coefficient on the interaction term as the level of a particular brokerage firm's academic sophistication

– a positive coefficient suggests that as stock anomaly score increases, recommendation levels from the brokerage firm also increase. We then sort all the brokerage firms into quartiles based on the academic sophistication measure and track the characteristics of each quartile over the subsequent four quarters. We find that after two quarters following the formation date, the "sophistication" measure of each brokerage quartile loses statistical significance (i.e., they are not statistically different from zero) in the recommendation sample, suggesting brokerage firms do not possess persistent skill to process anomalies in their stock recommendations. In contrast, we find the bottom one quartile brokerage firms, who are identified as non-academically sophisticated, persistently issue target price that are against anomaly prescriptions over the subsequent four quarters. Meanwhile, the brokerage firms initially assigned as academically sophisticated do not show persistent skill to process anomaly characteristics correctly in the subsequent quarters. These findings are consistent with the view that analysts are not skilled at incorporating anomalies in their research. We show that a trading strategy which follows investment advice by non-sophisticated brokerage firms generate negative abnormal returns, suggesting that sell-side analysts could improve the value of their research by incorporating stock market anomalies in their research process.

Our paper contributes to the knowledge of inputs in sell-side analysts' research processes. An extensive analyst literature has investigated whether analysts' research possesses valuable information. Literature has examined whether information from financial statements are incorporated into analysts' research outputs. However, due to the unobservable nature of analysts' analysis, it's not completely clear what other inputs analysts use in their decision processes, a question referred as the "black box" by Bradshaw (2011). Several recent studies provide direct evidence and provide insights into the "black box". Brown, Call, Clement and Sharp (2015) conduct surveys and interviews with analysts and show that private communication with management is more important than firms' 10K filings when analysts forecast earnings and make recommendations. Bradley, Gokkaya, and Liu (2017) document that institutional investors value analysts' industry experience and expertise greatly. This paper adds to the literature by investigating whether sell-side analysts, who are expected to provide sound investment advice to investors, use return-predicting anomaly characteristics in their research.

This paper also adds to the literature on how market participants react to anomalies. McLean and Pontiff (2016) show that the post-publication profitability of anomaly variables is 58% lower than the magnitude documented during the academic study sample period, suggesting that investors learn from published anomalies. Studies have examined how different market participants' react to anomalies. Wu and Zhang (2015) show that short sellers use anomaly-based strategies to short overpriced firms and avoid underpriced firms. Edelen, Ince and Kadlec (2016) show that institutional investors in aggregate trade contrary to anomaly prescriptions. Contemporaneous work by Engelberg, McLean and Pontiff (2018) examine 96 anomalies and find that analysts' consensus recommendations and target prices tend to be in conflict with anomaly variables. Our paper differs in methodology and also in that we investigate whether anomaly processing skills are more evident in some segments of the analyst population. We do not investigate the risk and behavioral explanations for anomaly variables, however our findings are consistent with the explanation that analysts are likely subject to biased expectation that could contribute to stock mispricing.

The rest of the paper is organized as follows: section II discusses related literature and develops hypotheses. Section III describes data and variable construction. Section IV presents test design and empirical results. Section V concludes.

2. Literature Review and Hypotheses Development

Extensive literature has documented various variables that predict cross sectional future return. Despite the debate whether stock anomalies are mispricing or risk factors, the significant relation between anomaly variables and future stock returns provide incentive to use anomaly variables to predict future stock returns. Academic studies are interested in what information analysts use in their research process. Prior studies and survey suggest that sell side analysts incorporate both macro level and micro level information in their research output. Findings in Howe, Unlu and Yan (2009) show that aggregate analyst recommendations (i.e., recommendation aggregate across all analysts all stocks) have predictability in future market and industry returns. Da and Schaumburg (2011) show that analysts' implied expected returns derived from their target price estimates provide valuable information for stocks within industry. Since analysts' research process is unobservable, studies have explored multiple information sources for sell-side analysts. For example, the early literature examine whether information in firms' financial statements are captured in analysts' earnings forecasts. Recent surveys indicate that communication with management are more valued by analysts than information in firms' annual report and analysts' industry expertise is highly valued by institutional investors. Besides information of industry outlook and firms' fundamentals, anomaly variables can facilitate the stock picking process.

Earlier accounting literature on analysts' research and market anomalies have examined the relation between analysts' earnings forecasts, cash flow forecasts and accounting anomalies such as post earnings announcement drift (PEAD) and accrual anomaly. These studies investigate questions such as whether analysts correctly recognize those anomaly characteristics and whether analysts' research mitigates anomalous returns. Some find positive evidence that analysts' research mitigate anomalous returns. For example, Zhang (2008) finds that market reacts more in the event window and less in the drift window with responsive analysts' forecast revision, suggesting prompt analysts' forecast revisions mitigates PEAD. Radhakrishnan, Wu (2014) show that accrual mispricing is less for firms having both earnings and cash flow forecast than for firms that only have earnings forecasts. Mohanram (2014) shows that the diminished returns to accrual-based strategies are related to more frequent and accurate analysts' cash flow forecasts. Other studies suggest that analysts have biased expectation that are related to anomalous returns. Bradshaw, Richardson, Sloan (2001) show that analysts' earnings forecasts do not incorporate the predictable future earnings declines associated with high accruals, which is negatively related to future stock returns. A later study by Bradshaw, Richardson, Sloan (2006) show a strong negative relation between firm's net external financing and future stock returns (i.e., net external financing anomaly) while analysts' forecasts are overoptimistic for firms with high net external financing. Amir, Kama and Levi (2015) show that both investors and analysts fail to recognize the contribution of different components of earnings to earnings persistence and it partially causes post-earnings announcement drift. Bouchaud et al. (2016) investigate quality anomalies (e.g., ratio of operating cash flows to assets) which indicates firms' profitability. They find that sell side analysts' forecast errors are negatively correlated to quality indicators and suggest that analysts are less attentive to firm's profitability indicators. Engelberg, McLean and Pontiff (2017) document that returns of 97 stock anomalies are 7 times higher on earnings announcement date and 2 times higher on corporate news day. They show that except anomalies based on valuation ratios, analysts' earnings forecasts are too low for stocks in the long leg of anomaly portfolios and too high for stocks in the short leg of the anomalies. Although the significant anomalous returns gives stock pickers the motivation to take advantage of anomaly characteristics in the decision process, the above studies suggest that analysts might have limited attention or access to the full information set and exhibit biased expectation to some extent. We propose the first hypothesis as following:

Hypothesis 1: Sell-side analysts' consensus recommendation and target prices are not correlated to stock aggregate anomalies

Analysts are not the same. Their research outputs are influenced by analysts' skill, information set and incentives. For instance, Bradshaw, Brown and Huang (2013) find statistically significant but economically weak evidence of persistent differential ability across analysts to forecast target prices. Hugon, Kumar, and Lin (2015) find that analysts' earnings research underreact to macroeconomic news, but analysts who have access to a macroeconomist employed by the same employer underreact much less. Lin, McNicols (1998) show that unaffiliated and affiliated analysts differ in the favoritism in recommendation and growth rate forecasts for firms went through underwriting. Ideally we would like to examine analyst level characteristics in terms of taking advantage of anomalies. However, due to the limited recommendations and target prices issued by an average analyst for an average covered firm each year, we propose a set of tests at the brokerage firm level.

Findings in prior studies suggest that there is shared information and resources within an organization or social circle. For example, Irvine, Simko, and Nathan (2004) show affiliated analysts make more accurate earnings forecast for firms heavily owned by the asset management department in the same brokerage firm. Such positive externality could be due to the interaction between the asset management department and research department within a brokerage firms. For example, affiliated analysts might have stronger incentive to better investigate firms to benefit the performance of the asset management department. The asset managers and analysts could also share information and ideas on these firms. Pomorski (2009) finds that shared trades (i.e., buy or sell the same stock) by multiple fund managers within the same fund management companies outperform benchmarks and other trades. Such shared trades are classified as “the best ideas” in Pomorski (2009) because they are generated by the shared information and research in the management company’s internal network. Pool, Stoffman and Yonker (2015) show that socially connected mutual fund managers who lives in the same neighborhood have similar holdings and trades, and a long short trading strategy based on trades shared by fund managers generate positive abnormal returns, suggesting value adding information through the network. We hypotheses that such shared resources or information also exist inside the research department within a brokerage firms. We believe this is a reasonable assumption because analysts within the same brokerage firms have the opportunity to work as a team and network as a group. Studies by Hugon, Kumar, Lin (2015) and Bradley, Gokkaya, Liu and Michaely (2017) show that access to in-house macroeconomists and policy analysts gives analysts an advantage to generate better quality research (e.g., less optimistic earnings forecasts and superior stock recommendations). If the shared information among analysts is related to anomaly strategies, recommendations and target prices issued by analysts within the same employer should be correlated to stocks’ anomaly variables. We expect to pick up such shared characteristic through brokerage firm fixed effects. The following is the second hypothesis.

Hypothesis 2a: In the cross section, brokerage firms exhibit different ability to persistently incorporate anomaly characteristics in recommendation and target prices

We next examine analyst characteristics that have been shown to be associated with better skill — analyst’s experience and “All-star” designation. Studies have shown that analysts with more experience are more accurate (Clement (1999), Mikhail, Walther, Willis (1997), Mikhail, Walther, Willis (2003)). Institutional Investor’s star analysts are found to provide more accurate earnings forecasts and more value adding stock recommendations by Stickel (1992) and Desai, Liang and Singh (2000)). However, whether analysts with more experience or "All-star" title are academically sophisticated in their research is an empirical question and investigating this question furthers our understanding of this research question.

Hypothesis 2b: In the cross section, analysts' characteristic such as experience and "All-star" title are associated with ability to incorporate anomaly characteristics in recommendation and target prices

For practitioners and investors, brokerage firms' ability to persistently take advantage of anomalies matters if such ability increases the quality and value of analysts' research. We show that a long short strategy which follows anomaly prescription generates both statistically and economically significant positive abnormal returns. Such abnormal return suggests incorporating anomalies could impact the investment value of analysts' output. However, not being consistent with anomaly prescription doesn't necessarily indicate that recommendations and target prices are of less investment value. To investigate whether anomalies could have real impact on the value of analysts' research, we examine the profitability of following investment advice (through recommendation or target price) by both academically sophisticated and non-sophisticated brokerage firms. This leads to our third hypothesis.

Hypothesis 3: The ability to incorporate anomaly characteristics in the analysis impact the profitability of recommendation and target prices positively.

3. Data

Data used in this paper comes from three sources. Firms' financial data are obtained from Compustat, while stock prices, returns, and volumes are from CRSP. We obtain analysts' recommendations and target prices from the Institutional Broker Estimate System (I/B/E/S). Due to restrictions in the availability of data from IBES, all analyses using analysts' recommendations are restricted to sample dates from 1993 and 2016, whereas analyses involving target prices are from 1999 to 2016. Observations with unidentified analyst names are excluded from the analysis.

3.1 Anomalies replication and aggregate score

We replicate the methodology employed in Edelen et al. (2016) to construct an aggregate measure for seven prominent anomalies found in the academic literature. The set of anomalies includes net operating assets (NOA), gross profitability (GP), investment-to-assets (IVA), Ohlson Score (O-score), book-to-market (BM), undervalued minus overvalued (UMO) and momentum. The sample includes US common stocks listed on the NYSE, AMEX and NASDAQ, and excludes utilities, financials, and stocks whose prices are less than $5.

We construct stock characteristics (i.e., *net operating assets*, etc.) for each separate anomaly following prior literature and detail these variables in Table 1.12. We then replicate the methodology used in Edelen, et al (2016). For five of the seven anomalies (excluding momentum and undervalued-minus-overvalued), we do the following: in June of each calendar year (t) we sort stocks into quintile portfolios based on anomaly characteristics obtained from accounting information at the end of year t-1.[2] We assign each quintile a value between -2 and +2, where -2 (+2) is assigned to the quintile portfolio that anomaly prescriptions suggest investors should take a short (long) position. For undervalued-minus-overvalued, in each June in calendar year (t) we sort stocks into long, short and neutral portfolios based on firm's financing in fiscal year t-2 and y-1. We assign value 2, -2 and 0 to the long, short and neutral portfolios respectively. For momentum, we amend this methodology slightly by updating quintile portfolio sorts each quarter (rather than in June of each year) based on stocks' prior 12 month returns. We then follow each quintile portfolio over the subsequent 12 month period (ending in June of year t+1).[3] Holding period returns are value weighted as in Edelen et al. (2016) and are presented in Table 1.10. We find that across the seven different portfolios, the "long" portfolio outperforms the "short" portfolio by between 1.06% and 2.42% per quarter when using Fama and French three-factor alphas.

Since anomaly characteristics are not perfectly correlated, we conjecture that an investor might be better off by aggregating these anomaly characteristics into a single measure (consistent with McLean and

[2] Edelen, et al (2016) use tercile portfolios rather than quintile portfolios in their paper. We replicate their paper exactly and present anomaly portfolio returns in Table 1.11. Returns reported in Table 1.11 are quantitatively similar to those reported by Edelen.

[3] For momentum portfolios, we form new quintile portfolios each quarter and skip one month between the portfolio formation date and the measurement of portfolio returns. The holding period for momentum portfolios is 3 months.

Pontiff (2016) and Edelen, et al (2016)). We proceed by calculating an aggregate "anomaly score" for each stock in each quarter. Our aggregate score sums the quintile assignments – where a quintile assignment has a value from -2 (short) to +2 (long) – across all anomalies that we consider.[4] As such, our aggregate anomaly score is bounded between -14 and +14. A more detailed description of this aggregation process (and the associated timeline) is presented in Figure 1.1 and Figure 1.2. We present summary statistics for the aggregate score in Table 1.1. The average score has a mean (median) value of .9658 (1.0976). We also find significant amounts of variation. The value for the 25th percentile is -1.43 and the value for the 75th percentile is 3.59. In subsequent tests we partition sample firms into quintile portfolios based on the aggregate score ("aggregate score rank"). We show that these ranks are informative for future abnormal returns as the difference in performance between extreme quintiles is 2.49% per quarter (see Table 1.10) using Fama and French three-factor alphas.

3.2 Analysts' outputs

3.2. 1. Recommendation

Our research agenda is to ascertain whether sell-side analysts incorporate anomaly information when they provide information to clients. In particular, we believe that the analyst outputs most likely to be influenced are an analyst's recommendations and target prices. We obtain analysts' recommendations (buy, hold, sell) from the Institutional Brokerage Estimates System (IBES) during the period from 1992 until 2016. Since our unit of analysis for anomalies is at the stock-quarter level, we match this for analysts' recommendations by calculating an average recommendation score across all analysts that follow a particular stock in each quarter. Specifically, we include only the most recent recommendation from each

[4] For example, if a stock has a B/M ratio that is in the top (e.g. long) quintile and an O-score that is in the middle quintile in a particular quarter, then that stock's aggregate score across these two anomalies would be +2 (this equals a +2 value for the B/M quintile and a 0 value for the O-score quintile).

analyst and require the recommendation be issued within the past 12 months (see Jegadeesh, Kim, Krische, and Lee (2004), Howe, Unln, Yan (2009)).[5] Specifically, we use the following equation:

$$REC_{i,q} = (\sum_{j=1}^{n} rec_{i,j})/n \tag{1}$$

where $REC_{i,q}$ is the average recommendation, i and q denote the stock and quarter, and n is the number of distinct analysts. *Rec* takes a value between 5 and 1, where 5 indicates a strong buy recommendation and 1 indicates a strong sell recommendation. Table 1.1, Panel A shows that the average stock has a consensus recommendation of 3.74 (which is above hold and close to buy), consistent with findings in prior studies that analysts' recommendation are optimistic (Cowen, Groysberg, and Healy (2006)).

3.2. 2. Target Price

While our investigation of analysts' recommendations has the benefit that it conveys an unambiguous endorsement, there are also some weaknesses. First, recommendations have been shown by prior research to be upwardly biased (Lin, McNichols (1998), Michaely, and Womack (1999)), as evidenced by the fact that only about 10% of total recommendations are in the categories sell or strong sell. Second, recommendations are categorical and might lack the necessary granularity to uncover the proposed relation. Fortunately, we also have access to analysts' price targets. Price targets represent an analyst's expectation of stock price movements over the subsequent 12 month period. As such, price targets can be used to calculate an analyst's expected / implied return (IRET) for a stock as follows:

$$IRET_{i,j,q} = \left(\frac{TP_{t,j,i}}{P_{t-1}}\right) - 1 \tag{2}$$

where i and j refer to the firm and analyst, and $TP_{t,j,i}$ is the most recent target price issued by analyst j during the previous 12 months before the end of quarter q. P_{t-1} is the stock price on the day prior to the

[5] During our sample period, the average analyst issues 1.33 recommendations (2.49 target prices) each year for the average firm that s/he covers.

Target Price announcement date (t). The prior day stock price is used as the denominator to avoid influence of analysts' announcements on stock prices on the announcement day[6]. Both $TP_{t,j,i}$ and P_{t-1} are split adjusted using stock split factors from CRSP. We then take the average implied return for each stock and quarter across all analysts that have issued a target price in the previous 12 months. As reported in Table 1.1, Panel B, the average stock has an implied return of 23.95%, which is similar to values reported by prior studies (Bradshaw, Brown and Huang (2013)).

3.3 Sample descriptive statistics

Table 1.1 shows the summary statistics for recommendation and target price samples separately. Summary statistics are from the sample after merging stock anomaly information, analysts' recommendation (or implied return), and control variables. We calculate the distribution of each variable across all the firms each quarter and report the time series average, median, 25th percentile, 75th percentile, and standard deviation of each variable. Each quarter, there are on average about 1131 firms, 229 brokerage firms, and 2765 analysts each quarter in the full recommendation sample between 1994 and 2016. At the end of each quarter, each brokerage firm is associated with an average of 15.4 analysts, each of whom issue recommendations for an average of 7.4 firms in 2.6 industries. In the target price sample, there are on average 9.1 firms covered by 2807 analysts each quarter.

The firms in the recommendation and target price samples are comparable in terms of characteristics such as firm size (market capitalization), stock trading volume and institutional ownership. For example, the average firm size is 6.98 billion in the recommendation sample and 7.36 billion in the target price sample.

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[6] The empirical findings are robust for implied return measure where the denominator is the announcement month end stock price or quarter end stock price.

4. Empirical Results

4.1 Univariate test

Table 1.2 reports the univariate test[7]. Each quarter we sort stocks into quintile groups based on their *aggregate anomaly score* and report the average analyst recommendation for each quintile in Panel A. We find that the short anomaly portfolio receives an average recommendation of 3.768 (between a buy and hold), while the long anomaly portfolio receives an average recommendation of 3.759. We report the difference between the long and short legs is -0.008 (t-statistic=-0.45), suggesting that recommendation levels are not significantly different between the long and short legs.

Since recommendation levels are potentially biased by conflicts of interest in the analyst-broker relationship (Michaely and Womack, 1999), one might expect that analysts (if they are paying attention to anomalies) revise their recommendations in an appropriate manner. To test this conjecture, we draw from the methodology of Edelen et al (2016) and calculate changes in analysts' consensus recommendations from before anomaly variables are calculated (six quarters prior) to the current quarter – the methodology is illustrated in Figure 1.3. The consensus recommendation of the short anomaly portfolio decreases by 0.170 while the consensus recommendation of the long anomaly portfolio increases by 0.056. We report the difference between the long and short legs is 0.272 (t-statistics=9.82). Our results strongly suggest that analysts are revising their recommendations in the correct direction, but the adjustment is incomplete.

We repeat our analyses in a restricted sample of observations where we require the same analyst to issue a recommendation for a particular stock in both periods (six quarters prior and the current quarter). Statistics in the restricted sample are consistent with findings in the full sample. The short anomaly portfolio receives an average recommendation of 3.647 while the long anomaly portfolio receives an average recommendation of 3.639. The difference between the long and short legs is -0.008 (t-statistic=-0.45). The

[7] The statistics are generated in the sample before merging control variables.

consensus recommendation of the short anomaly portfolio decreases by 0.154 while the consensus recommendation of the long anomaly portfolio increases by 0.045. The difference between the long and short legs is 0.199 (t-statistics=7.18).

In Table 1.2, Panel B, we repeat our univariate statistics for implied returns derived from analysts'' target prices. We find that the short anomaly portfolio receives an average implied return of 33.36%, while the long anomaly portfolio receives an average implied return of 23.78%. The difference between the long and short legs is -9.58% (t-statistic=-6.32), suggesting that implied returns are statistically higher for the short leg of the anomaly portfolio. We again test the restricted sample and find consistent inference. The difference between the long anomaly portfolio (average implied return is 30.32%) and the short anomaly portfolio (average implied return in 20.52%) is -9.80% (t-statistic=-6.71). Overall, our univariate findings present clear evidence that analysts' target price estimates are in the opposite direction of what anomaly prescription would suggest.

One might expect analysts to have consistent views for a particular stock in all of their external communications with firm clients. As such, it is curious that analysts' recommendations do not seem to be associated with anomaly prescriptions, while target price forecasts are opposite. One possibility for this apparent contradiction is that the above univariate tests are conducted at consensus level in two separate samples and the composition of analysts included in the consensus measures are not the same. In order to flesh out our result, we investigate the relation between target prices and anomaly variables after conditioning on the recommendation level (i.e., holding recommendation levels constant).

We include only analysts who issue both a recommendation and target price for the same firm in the same quarter (outputs issued over the prior 12 months). We then parse all observations by recommendation level (e.g., strong buy) and within each recommendation level group we sort stocks each quarter into quintile portfolios based on their aggregate anomaly score rank. Table 1.3 reports the average implied return for each aggregate score quintile portfolio conditional on each recommendation level between 1999 and 2016. In the strong buy recommendation group, the short leg portfolio has a median (mean) implied return of 36.93% (42.05%) while the long leg portfolio has a median (mean) implied return of 28.76% (30.35%). The same negative relation between aggregate anomaly quintile rank and average implied returns also shows up in both buy and hold recommendation groups. Although we find a less clear pattern between aggregate anomaly scores and average implied return in the sell (or strong sell) groups, we are cautious in our interpretation of these patterns since both sell and strong sell categories contain a very small number of recommendations (approximately 90% of our observations are in the strong buy, buy, and hold categories).

The above findings suggest that analysts' recommendations are not associated with anomaly prescriptions while their target price estimates are negatively correlated with what anomalies would prescribe. However, such inference might be incorrect due to potential omitted variables. Therefore, we next investigate the relationship between stock recommendation (and implied returns) and anomaly characteristics while controlling for variables that have been found to be correlated with analysts' recommendation or implied return by prior studies.

4.2 Multivariate tests

Prior studies have documented variables that could explain stock recommendations. For example, Jegadeesh, Kim, Krische, and Lee (2004) show that firms with positive earnings surprises and high sales growth are associated with favorable stock recommendations. Bradshaw (2004) shows that long term growth rate has the greatest explanatory power to recommendations and favorable recommendations are likely to be justified by price-earnings ratio. Jackson (2005) documents that stock recommendations are impacted by the conflict faced by sell-side analysts, the conflict between building their reputation and issuing optimistic research to generate short term trading commissions. Ljungqvist, Marston, Starks, Wei, and Yan (2007) find that analysts' recommendation relative to consensus is negatively associated with the presence of institutional investors. We follow findings from these studies and control for variables that are correlated to stock recommendations, including firms' sales growth, earnings-to-price ratio, standardized unexpected earnings (SUE), firm size, total accrual, stock trading volume and institutional ownership[8]. Table 1.4 reports the multivariate regression where the dependent variable is analysts' consensus recommendation of a particular stock ($REC_{i,t}$) or its change over the past six quarters ($\Delta REC_{i,t}$). We choose Tobit regression because stocks' consensus recommendations are not discrete and are bounded between 1 and 5. Specifically, we run the following regression (3), where i and t refer to firm and quarter:

$$REC_{i,t}\ (or\ \Delta REC_{i,t}) = \alpha + \beta_1 aggregate\ score\ rank_{i,t} + \beta_2 sales\ growth_{i,t} + \beta_3 total\ accural_{i,t} + \beta_4 SUE_{i,t} + \beta_5 Volume_{i,t} + \beta_6 Institutional\ ownership_{i,t} + \beta_7 size_{i,t} + \beta_8 \frac{earnings}{price}_{i,t} + quarter\ dummies \tag{3}$$

We find that aggregate score rank is positively associated with the consensus recommendation level. However, the economic magnitude of the association is not significant. Specifically, as aggregate score rank increases by one standard deviation, the consensus recommendation level increases by 0.014, which is small compared with its standard deviation 0.556. Prior studies (Edelen, Ince and Kadlec (2016)) on stock market anomalies show that the performance of long and short legs of anomaly differ. Their findings suggest that the short leg of anomaly contributes more to risk adjusted abnormal return potentially due to short sell constraint, we next investigate whether analysts process anomaly characteristics differently for stocks in the long and short legs of the anomaly. We group stocks into long (short) leg if their aggregate score ranks are in the top (bottom) two quintiles. We then run regression (3) in each of the two sub samples respectively. The results show that the positive association between anomaly score rank and stocks' consensus recommendation is statistically significant for stocks in the long leg. In contrast, anomaly characteristics are not associated with analysts' consensus recommendation for stocks in the short leg. Consistent with findings in the univariate test, we find that *aggregate score rank* is positively associated

[8] Table 1.4 does not include analysts' long term growth rate and analysts' revision in earnings forecast as in Jegedeesh, Kim, Krische and Lee (2004). These two variables as analysts' research output are likely correlated to control variables in the right hand side of the regression. The regression results are robust if we add them as controls.

with changes in stock's consensus recommendation ($\Delta REC_{i,t}$) over prior six quarters. Column (4) to (6) in panel A of table 1.4 reports the multivariate regression where the dependent variables is the change in consensus recommendations. We find a positive association between changes in consensus recommendation and aggregate score rank. The association is statistically significant in both long and short subsamples. Specifically, the consensus recommendation of an average stock in the strong buy group at quarter t increased by 0.071×2=0.142 (t-statistic=6.33) over the past six quarters while the consensus recommendation of an average stock in the strong sell group at quarter t decreased by 0.057×2=0.114 (t-statistic=5.97) over the past six quarters[9].

The above tests are conducted in the full sample, including both revisions and first-time issued recommendations. In other words, analysts who issued recommendations by the end of quarter t could be different from those who issued recommendation for the same stock six quarters ago, hence the change in consensus recommendation over the six quarters could include unobservable analyst characteristics that we cannot control for. To eliminate the influence by analysts' characteristics, we conduct the same multivariate regression in the restricted sample. The restricted sample requires the analyst to issue recommendations over the 12 months prior to quarter t-6 and quarter t, hence the change in consensus recommendation removes the impact of time-invariant analysts' characteristics on stocks' recommendation. The restricted sample also removes the impacts from initiation and drop of analyst coverage. For example, Irvine (2003)) suggest that initiation and stop of analysts' coverage have more information than revisions of existing recommendations. McNichols and O'Brien (1997) show that analysts tend to stop coverage instead of issue

[9] In unreported tests, we regress consensus stock recommendation (or its change over prior six quarters) on each anomaly separately. Analysts' consensus recommendations are negatively associated with four of the seven anomalies and are not associated with two of the seven anomalies. The changes of consensus recommendations are positively associated with five out of the seven anomalies examined in this paper. We next include *post publication dummy* for each anomaly and the interaction between anomaly score and *post publication dummy* in the regression. We do not find evidence that analysts become academically sophisticated after anomalies are made public.

sell recommendations for firms they view unfavorably. We report the restricted sample results in panel B of table 1.4.

Findings in the restricted sample are consistent with those in the full sample. As aggregate score rank increases by one standard deviation, the consensus recommendation level increases by 0.011 (=1.3537*0.008), which is small compared with its standard deviation 0.683. In the subsamples, the positive association between consensus recommendation level and aggregate score rank is marginally significant in the long leg and not significant in the short leg. The association between aggregate score rank and change in consensus recommendation level over prior six quarters are statistically significant in both long and short subsample. Specifically, the consensus recommendation of stocks in the strong buy group increased by 0.049×2=0.098 (t-statistic=3.23) over the past six quarters while the consensus recommendation of stocks in the strong sell group decreased by 0.047×2=0.094 (t-statistic=2.86) over the past six quarters. The smaller economic magnitude in the restrictive sample suggests that analysts' initiation (drop) of coverage and aggregate score rank is positively (negatively) associated.

Besides examining analysts' stock recommendations, we also investigate another important research output by sell-side analysts, target price estimates, which has been found to possess information beyond earnings forecast and stock recommendation by prior studies (Brav and Lehavy (2003)). In addition to the additional information, target prices' continuous nature allows tests to pick up information that could be missing in discrete stock recommendations. To control for variables that are correlated to analysts' implied returns (derived from target prices), we follow Dechow and You (2013) who examine determinants of errors in implied returns (derived from target price estimates). They find three sources of explanatory variables: analysts' fundamental forecasts, stocks' risk characteristics and analysts' incentives. Based on their findings, we include the following control variables in the multivariate regression for analysts' consensus implied returns. Analysts' fundamental forecasts include realized earnings forecast errors, long term growth rate revisions and dividend yield. Stock risk profiles include Amihud illiquidity, size, and idiosyncratic volatility. Variables proxy for analysts' incentives are stock trading volume, institutional ownership and firm's external financing. We also include 52-week high dummy to account for analysts' anchoring effect (Li, Lin, Lin (2016)). We run the following OLS regression model (equation (4)) and cluster standard errors at firm and quarter level, where $iret_{i,t}$ is the consensus implied return for stock i at quarter t.

$$IRET_{i,t} = \alpha + \beta_1 aggregat\ score\ rank_{i,t} + \beta_2 Institutional\ ownership_{i,t} + \beta_3 52\ week\ high\ dummy_{i,t} + \beta_4 size_{i,t} + \beta_5 Dividend\ yield_{i,t} + \beta_6 Idiosyncratic\ volatility_{i,t} + \beta_7 Amihud\ illiquidity_{i,t} + \beta_8 volume_{i,t} + \beta_9 External\ Financing_{i,t} + \beta_{10} realied\ earnings\ forecast\ errors_{i,t} + \beta_{11} long\ term\ growth\ revision_{i,t} + quarter\ fixed\ effect \quad (4)$$

Table 1.5 reports the results for regression (4). In both full and restricted samples, an average stock's consensus implied return is negatively associated with its *aggregate score rank.* The negative association is statistically significant across model specifications in different samples. As a stock moves from strong sell (bottom aggregate score rank) to strong buy (top aggregate score rank), the consensus implied return decreases by 0.013×4=5.2%, suggesting that analysts in aggregate consider an undervalued stock (i.e., a strong buy by anomaly prescription) as overpriced. If anomaly prescription generates significant abnormal return, trades based on target price estimates that are contrary to anomaly prescription could hurt investor's value. Indeed, we show that a value weighted long short strategy that follows anomaly prescription, namely longs stocks in the strong buy and shorts stocks in the strong sell generates a quarterly Fama French alpha of 2.49%, or a 10.34% annually alpha[10] (data is Table 1.10). These findings suggest that sell-side analysts in aggregate are wrong about the direction of future return with non-trivial economic magnitudes[11].

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[10] A similar long short strategy based on aggregate score rank of stocks that have analyst coverage generates statistically significant annual Fama French three factor alpha of 9.92% in recommendation sample and 6.81% in target price sample.

[11] In unreported tests, we regress consensus implied returns on each anomaly separately. Analysts' consensus implied returns are negatively associated with six of the seven anomalies in this paper. We next include *post publication*

4.3 Brokerage level tests

So far, we treat sell-side analysts as an entity and examine their recommendation and target price in the aggregate level. However, analysts are heterogeneous in the cross section. Both academic research and financial press have documented differences in performance and value generated by analysts. For example, some analysts (star analysts) are valued by buy side institutional investors more than non-star analysts. Sorescu and Subrahmanyam (2006) document different market reactions to high and low quality analysts. Ideally we would like to examine the cross sectional heterogeneity in terms of processing anomaly characteristics among analysts. However, due to the small number of recommendations and target prices issued by individual analysts each year, it's not feasible to conduct tests with sufficient statistical power to draw the inference. Instead, we conjecture that there is shared information among sell-side analysts who are affiliated to the same brokerage firm. Prior studies (Irvine, Simko, Nathan (2004), Pomorski (2009), Pool, Stoffman and Yonker (2015)) show evidence that suggests shared (value-adding) information among people within business environment and social settings. Studies also show that access to in-house macroeconomists (Hugon et al. (2015)) and in-house Washington Policy analysts (Bradley et al. (2017)) gives sell-side analysts an edge to provide better quality research, suggesting shared information in brokerage firm's internal network.

4.3.1 Persistence or academic sophistication at brokerage firm level[12]

To examine brokerage firms' academic sophistication, we first identify whether research outputs from a brokerage firm are conform or contrary to anomaly prescription by running the following Tobit model (regression (5)) each quarter.

dummy for each anomaly and the interaction between anomaly score and *post publication dummy* in the regression. We do not find evidence that analysts correctly incorporate anomalies after publication.

[12] We conduct persistence tests for brokerage firms in the tails and the results are consistent with findings in the main sample.

$$REC_{i,j,q} = \beta_1 Aggregate\ score\ rank_{i,q} + \beta_2 brokerage\ firm\ fixed\ effects_n \qquad (5)$$

$$+ \beta_3 brokeage\ firm\ fixed\ effects_n \times Aggregate\ score\ rank_{i,q}$$

$$+ \sum \beta_m controls_{i,q} + \varepsilon$$

where $REC_{i,j,q}$ is the most recent recommendation issued by analyst j for stock i over the 12 months prior to the end of quarter q, $brokerage\ firm\ fixed\ effects_n$ is a series of dummy variables for brokers in the sample. The dummy variable for the brokerage firm n[13] is one if analyst j who issued the recommendation is affiliated with broker n when the recommendation was issued. $Brokeage\ firm\ fixed\ effects_n \times Aggregate\ score\ rank_{i,q}$ is the interaction between the dummy variable of brokerage firm n and the stock's aggregate score rank in quarter q. The interaction coefficient β_3 is a measure of academic sophistication. A positive value of the interaction coefficient β_3 means that the recommendation issued by brokerage n is positively associated with stock i's aggregate score rank, suggesting brokerage firm n correctly process anomaly characteristics in the stock recommendation. A close to zero β_3 suggests the recommendation from the brokerage firm is not related to anomalies, suggesting brokerage firm n does not pay attention to anomalies. A negative β_3 suggests the brokerage firm is acting against anomaly prescription. We collect the coefficients β_3 for each brokerage firm each quarter over the sample period and examine the persistence of academic sophistication (β_3) in the following steps.

The idea is to sort brokerage firms into groups based on their academic sophistication measure (β_3) and then track the characteristics of each group. By doing this, we answer the question how the average "sophistication" measure of each group change over the subsequent quarters. Specifically, at quarter q, we sort all the brokerage firms into quartiles based on their interaction coefficients β_3. Brokerage firms in the bottom quartile are labeled as non-academically sophisticated and those in the top quartile are labeled as

[13] To be included in the sample, each brokerage firm need to issue recommendations (target prices) to more than ten (five) firms in a quarter. We suppress the constant term so that there is no base level in the brokerage firm fixed effects.

academically sophisticated. We then compute the average interaction coefficients (β_3) across all the brokerage firms in each quartile from quarter q (the formation quarter) to quarter q+4[14]. Table 1.6 reports the time series mean of the "sophistication" measure for each quartile brokers from the formation quarter q to the subsequent four quarters. Specifically, the bottom quartile (Q1) brokerage firms have an average interaction coefficient β_3 of -0.2707 (t-statistic=-10.04) in the formation quarter, suggesting recommendations from these brokerage firms are in the opposite direction as anomalies prescribe. The top quartile (Q4) brokerage firms have an average interaction coefficient β_3 of 0.2970 (t-statistic=12.09) in the formation quarter q, suggesting recommendations from these brokerage firms are consistent with anomaly score ranks. However, the "sophistication" measures are not statistically different from zero after two quarters subsequent to the formation quarter. The difference in the "sophistication" measure between non-academically sophisticated brokers (bottom quartile brokers) and academically sophisticated brokers (top quartile brokers) is not statistically different from zero by quarter q+4[15], suggesting no persistent skill of processing anomaly variables in the cross section of brokers. We also keep track of the retention ratio of each broker quartile over time. One quarter after the formation period, the retention ratios of each quartile range around 40% to 50%. By the end of quarter Q+4, only about 30% of the brokerage firms stay in the quartile that they are originally assigned in the formation quarter.

We next follow the same method and examine persistent skill in the target price sample. We run the following OLS regression (equation (6)) each quarter, where $IRET_{i,j,q}$ is the implied return by analyst j for stock i in quarter q. $IRET_{i,j,q}$ is computed as in equation (1).

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[14] We record the average number of brokerage firms in each quartile over time. A brokerage firm temporarily leaves the sample in quarters when it had no recommendation in the prior 12 months (the reason that the number of brokerage firms in each quartile differ in subsequent quarters).
[15] We note that Q+4 is the quarter we should focus on for detecting persistence because the dependent variable in the regression include the most recent recommendations by each analyst over the past 12 months.

$$IRET_{i,j,q} = \beta_1 Aggregate\ score\ rank_{i,q} + \beta_2 brokerage\ firm\ fixed\ effects_n \\ + \beta_3 brokeage\ firm\ fixed\ effects_n \times Aggregate\ score\ rank_{i,q} \\ + \sum \beta_m controls_{i,q} + \varepsilon \quad (6)$$

Table 1.7 reports the persistent test results in the target price sample. We find that a group of brokerage firm persistently generate target prices that are in the opposite direction as anomaly prescribes. In the formation quarter, the top quartile brokerage firms (academically sophisticated brokers) have an average β_3 of 0.0523 (t-statistic=7.92), suggesting implied returns derived from target prices issued by these brokerage firms are consistent with aggregate anomaly prescription. The bottom quartile of brokerage firms (non-academically sophisticated brokers) have an average β_3 of -0.0788 (t-statistic=-9.88), suggesting these brokerage firms act against anomalies in their target price estimates. Different from results in the recommendation sample, in the target price sample brokerage firms in the bottom quartiles keep providing target prices that are against anomaly prescriptions over the subsequent four quarters. The difference in β_3 between academically sophisticated (top quartile) and non-academically sophisticated (bottom quartile) brokers are positive and significant throughout the following four quarters after the formation quarter. We show that it's the bottom quartile brokers that drive such difference. These findings are consistent with those in the previous univariate and multivariate tests, where the *aggregate score rank* and consensus implied returns are negatively correlated. In the cross section of brokerage firms, instead of finding brokerage firms that are academically sophisticated, we find a group of brokers persistently act against anomalies.

4.3.2 Profitability of recommendations or target price issued by brokerage firms

Although brokerage firms may issue recommendations or target prices that are not consistent with anomaly prescriptions, it does not necessarily mean that these recommendations or target prices have no investment value. It's an empirical question whether being anomaly savvy is associated with high quality of stock recommendation and target prices estimates. We next examine the profitability of the recommendation (and target prices) issued by brokerage firms with different academic sophistication.

We follow the method in Barber, Lehavy, McNichols, and Trueman (2001) and create buy/sell portfolios indicated by (non-) academically sophisticated brokers. As we did previously, at the end of quarter t, we sort all the brokerage firms into quartiles based on each brokerage firm's "sophistication" measure β_3 from regression (5). We then go to quarter t+1, for each stock we compute the average of recommendations issued by academically sophisticated brokerage firms (i.e., the top quartile brokerage firms). Specifically, we include the outstanding recommendations issued in quarter t+1 by academically sophisticated brokers to compute the average recommendation. Next we sort all the stocks into terciles based on the average recommendation. The bottom tercile stocks are labeled as sell and the top tercile stocks are labeled as buy. We then compute the monthly stock returns in quarter t+2 for the buy and sell group stocks[16]. We next repeat the above steps and compute the monthly stock return for the buy and sell recommendations by non-academically sophisticated brokerage firms (i.e., the bottom quartile of brokerage firms sorted in quarter q). Panel A of Table 1.8 reports the Fama French monthly alphas of each portfolio.

We find that a long short strategy based on recommendations from non-sophisticated brokers generate negative Fama French monthly alpha of -33 basis points (t-statistic=-2.19). Specifically, the sell portfolio based on recommendations issued by non-academically sophisticated brokerage firms generates a monthly Fama French alpha of 16 basis points (t-statistic=1.55) in the subsequent quarter while the buy portfolio based on recommendations by these brokerage firms generate a monthly Fama French alpha of -18 basis points (t-statistic=-1.67). In contrast, we find that a similar long-short strategy based on recommendations issued by academically sophisticated brokerage firm do not generate alphas that are significantly different from zero.

We next examine the profitability of trades following the implied returns (derived from the target prices) by academically sophisticated and non-academically sophisticated brokers. The method is the same

[16] We value weight the monthly stock return using the stock's market capitalization at the end of quarter t+1.

as in the recommendation sample except that we use regression model (6). We report the results in panel B of table 1.8. We find that "sophisticated" and "non-sophisticated" brokerage firms do not differ with statistical significance. Specifically, the buy group stocks (i.e., those in the top implied returns tercile) suggested by non-academically sophisticated brokerage firms (i.e., brokerage firm who act against anomaly prescriptions) has a -54 basis points (t-statistic=-2.50) monthly Fama French alpha while the sell group stocks suggested by the same group of brokers has a -5 basis point (t-statistic=-0.49) monthly alpha. The trading strategy which longs the buy group stocks and shorts the sell group stocks generates a negative 49 basis points monthly alpha, which is not significantly different from returns generated by the same strategy based on suggestions from "sophisticated" brokerage firm. These findings are consistent with results from previous multivariate regression and persistence tests where no evidence suggests that brokerage firms could incorporate anomaly characteristics to improve the value of their research output.

4.4. Other cross sectional analysts' characteristics

Besides examining the cross sectional heterogeneity among brokerage firms, in this section we examine two characteristics of sell-side analysts, the "*Institutional Investor All-Star"* designation and analysts' experience. The *II all-star* analysts ranking has attracted a lot of attention from practitioners and academic research. It tells important information about sell side analysts' quality valued by buy-side institutional investors. All-star analysts are perceived by large buy side institutional investors as the most value adding among their peers. Prior studies have also shown that star analysts provide more accurate earnings forecast (Stickel (1992)) and outperforming stock recommendations (Desai, Liang and Singh (2000)). Studies have also documented that analysts' tenure is positively associated with high quality research (Clement (1999), Mikhail et al. (1997)). Therefore, we next run tests and examine whether these two analyst characteristics are associated with being anomaly savvy.

We hand collected the name and affiliation of All-star analysts between 2004 and 2016 from the October issue of Institutional Investor magazine. We manually match star analysts to I/B/E/S detailed recommendation and target price databases by their name, affiliated organization and the year they receive the award.

We create dummy variable *Star*, which is 1 for top three analysts in the annual Institutional Investor analyst ranking and 0 for the rest analysts. We also include analyst's special or general experience and its interaction with aggregate score rank in the regression. Analyst' special experience is the number of years an analyst covers a given stock. Analysts' general experience is the number of years an analyst have been in the I/B/E/S database. We include this analyst level characteristic to control for potential learning-by-doing (Mikhail, Walther and Willis (1997), (2003)). The interaction between special experience and stock's aggregate score rank measures whether analysts gradually pick up anomaly characteristics as s/he gain more experience with the stock. Each quarter, we run Tobit regression

$$REC_{i,j,t} = \alpha + \beta_1 Aggregate\ score\ rank_{i,t} + \beta_2 Star_j + \beta_3 Aggregate\ score\ rank_{i,t} \times Star_j + \beta_4 Analyst\ special\ experience_{i,j,t} + \beta_5 Aggregate\ score\ rank_{i,t} \times Analyst\ special\ experience_{i,j,t} + \sum \beta_m control\ variable^{17}{}_{i,t} \quad (7)$$

where $rec_{i,j,t}$ is the most recent recommendation issued by analyst j for stock i during the previous 12 months before quarter t, $Aggregate\ score\ rank_{i,t}$ is stock i's aggregate anomaly rank at the end of quarter t, and $Star_j$ is the dummy variable which is 1 if analyst j is among the top three II-All America research teams in the year to which quarter t belongs. Panel A in table 1.9 reports the Fama MacBeth regression results. The t statistics are generated by Newey-West adjusted standard errors with 4 lags. We find that star analysts are negatively associated with stock recommendation level. Specially, recommendations made by star analysts are 0.11 lower than recommendations made by non-star analysts on average, suggesting that star analysts are less optimistic and offer more conservative recommendations. The signs of the interaction term *Star* × *aggregate score rank* suggest that star analysts tend to issue recommendations that are in the opposite direction as anomaly prescribes. Specifically, as a stock's aggregate score rank increases by one star analyst on average reduces the recommendation by 0.016. Coefficients on special experience and its

[17] The control variables are the same as in regression (3).

interaction with aggregate score rank suggest that more experience is associated with less optimistic recommendation and more academic sophistication[18].

In the target price sample, we repeat the Fama Macbeth regression as in the recommendation sample, each quarter we run the following OLS regression,

$$IRET_{i,j,t} = \alpha + \beta_1 Aggregate\ score\ rank_{i,t} + \beta_2 Star_j + \beta_3 Aggregate\ score\ rank_{i,t} \times Star_j + \beta_4 Analyst\ general\ experience_{i,j,t} + \beta_5 Aggregate\ score\ rank_{i,t} \times Analyst\ general\ experience_{i,j,t} + \sum \beta_m control\ variable_{i,t} \quad (8)$$

where $iret_{i,j,t}$ is the implied return derived from the most recent target price issued by analyst j for stock i in the 12 months prior to quarter t. We report the time series means[19] of the coefficients from cross sectional regressions in panel B of table 1.9. Consistent with results in multivariate regression from Table 1.5, which shows that consensus implied return is negatively associated with stock's anomaly prescription, we find that *aggregate score ranks* are negatively associated with individual analyst's implied expected return, We also find that All-star analyst title is negatively associated with implied expected return, suggesting star analysts are less optimistic in their target price estimates. However, the coefficient on the interaction between star analyst and anomaly score rank is not statistically significant. Therefore, we do not find evidence that star analysts are academically sophisticated in terms of processing anomalies in their research. However, the coefficient on the interaction between aggregate score rank and analyst's general experience is marginally significant, suggesting more academic sophistication is associated with analysts' tenure in forecasting future stock price.

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[18] In a different model, we regress the consensus recommendation level on the average experience of analysts covering the stock and controls. The results show that the consensus recommendation level is positively associated with analysts' special experience.
[19] We compute t statistics with Newey-West adjusted standard error with 4 lags.

5. Conclusion

In this paper, we investigate the question whether sell-side analysts process anomaly characteristics in their recommendation and target price estimates. We first conduct tests at the aggregate level where we examine analysts' consensus stock recommendation and consensus implied returns. Evidence suggests that analysts correctly incorporate anomaly characteristics recommendation revisions, however the revisions are not sufficient. In contrast, at the aggregate level analysts issue target prices that are in the opposite direction as anomalies characteristics suggest. In other word, analysts in aggregate are optimistic (pessimistic) about stocks that are overvalued (undervalued) according to aggregate anomaly prescription. We next examine several segments of the analyst population and investigate whether there are cross sectional heterogeneity among analysts in terms of academic sophistication. Specifically, we find little evidence that brokerage firms possess persistent skill in terms of incorporating anomaly characteristics in recommendations or target prices. In addition, we show that a group of brokerage firms persistently issue target prices that are against stocks' anomaly prescription. A trading strategy that buys stocks favored by non-academically sophisticated brokerage firms (i.e., those issue recommendations or target prices that are in the opposite direction as anomalies suggest) and sell stocks not favored by these brokerage firms generate statistically significant negative monthly Fama French alphas. Lastly, we look into analysts' level characteristics such as the *Institutional investor All-star* title and analysts' experience. We find that star analysts either do not pay attention to anomaly characteristics (in the target price sample) or act against anomaly prescription (in the recommendation sample). Evidence suggest that analysts' experience are positively associated with academic sophistication.

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Appendix

Table 1.1 Summary Statistics

The following summary statistics are time series averages of each cross sectional mean, median, 25th percentile, 75th percentile, standard deviations and number of observations in each quarter. Restricted sample requires the analyst cover the same stock in the prior 12 months before quarter t-6 and before quarter t. We examine seven anomalies, including BM (book-to-market ratio), MOM (momentum), GP (gross profitability), IVA (investment-to-asset), NOA (net operating assets), UMO (undervalued minus overvalued) and OSC (Ohlson score). Each quarter, we sort stocks into quintiles based on their anomaly characteristics. Each individual anomaly rank has five values, namely -2, -1, 0, 1, and 2. Quintile 2 represents strong buy and quintile -2 represents strong sell. For each stock, *Aggregate Score* is the summation of individual anomaly ranks and has a value between -14 to 14 by construction. *Agg. Score rank* is the quintile rank based on stocks' aggregate score. *EP* is earnings-to-price ratio. *SUE* is standardized unexpected earnings. *Market cap* is stock market capitalization in millions of dollars. *Volume* is the rank percentile (between 0 and 1) based on stock's daily trading volume in its listed stock exchange. *Sales growth (SG)* is past four quarter revenues over prior four quarter revenues. *TA* is total accrual scaled by total assets. *52weekhigh dummy* equals one if the average stock return in quarter t is above the 95 percentile of the highest stock price in the past 52 week. *LTGREV* is the revision in consensus long term growth rate. *FY1_BIAS (realized earnings forecast errors)* is the difference between analysts' consensus one-year ahead EPS forecasts and the corresponding actual EPS, scaled by stock prices when the consensus target prices are computed. *Inst. own* is institutional ownership and firms with greater than 100% institutional ownership are excluded from the sample. *External financing* is the amount of external financing scaled by the average total assets. *Idio. Volatility* is measured by standard deviation of the residual in Fama French 3 factor regression using three month daily return data. *Illiquidity* is Amihud liquidity ratio over the 12 months preceding the current month. *REC* is the quarterly consensus recommendation level, which is the average of the most recent recommendations by each analyst over the prior 12 months. Δ*REC* is the change in consensus recommendation level from quarter q-6 to quarter q. *No. analysts broker* is the number of analysts from one brokerage firm who have at least one recommendation over the past 12 months. *No. industry broker* is the number of industries covered by a brokerage firm in the past 12 months. *No. firm broker* is the number of firms covered by a brokerage firm over the past 12 months. *No. firm* is the number of firms covered by an analyst over the last 12 months. *No. industry* is the average number of industries covered by an analyst in the past 12 months. *IRET* is the average of target price/stock price one day prior – 1. Only the most recent recommendation (target price) by an analyst over the past 12 months (one quarter) are included to compute *REC*, Δ*REC* and *IRET*. Utilities, financials and stocks with price less than $5 are excluded from the sample. Control variables (firm characteristics) are winsorized at 1% and 99% each quarter in the recommendation and target price sample, respectively.

Table 1.1 Continued

Variable	N	Mean	P25	P50	P75	St. dev	N	Mean	P25	P50	P75	St. dev
	Panel A Recommendation Full sample						Panel B Recommendation restricted sample					
Aggregate score	1131.1	0.9658	-1.4329	1.0976	3.5854	3.6543	692.7	1.1613	-1.0395	1.3421	3.6184	3.5146
Aggregate score rank	1131.1	-0.1071	-1.0976	-0.0122	1.0000	1.3762	692.7	-0.0449	-1.0921	-0.0132	1.0000	1.3537
BM rank	1131.1	-0.5709	-1.8720	-0.9878	0.2073	1.2291	692.7	-0.5775	-1.7632	-0.9671	0.1711	1.2219
Mom rank	1131.1	-0.0755	-1.0488	0.0000	1.0000	1.3774	692.7	-0.0854	-1.0461	-0.0132	1.0000	1.3474
GP rank	1131.0	0.5421	0.0000	0.7805	1.1220	1.0823	692.7	0.5041	-0.0461	0.4342	1.0395	1.0694
IVA rank	959.5	-0.0869	-1.0000	0.0000	1.0000	1.3436	578.3	-0.0178	-1.0000	0.0000	1.0000	1.3292
NOA rank	1114.6	-0.4129	-1.3232	-0.4573	0.6463	1.2477	685.4	-0.3726	-1.1316	-0.1974	0.6053	1.2075
OSC rank	1131.1	0.7343	0.0000	1.0000	2.0000	1.1481	692.7	0.7797	0.0000	1.0000	2.0000	1.1130
UMO rank	1054.6	0.8798	0.0000	1.4634	2.0000	1.3306	637.7	1.0077	0.0000	1.7105	2.0000	1.2883
Sales Growth (%)	1131.1	1.1726	1.0167	1.1057	1.2476	0.2987	692.7	1.1287	1.0047	1.0852	1.2030	0.2349
TA	1131.1	0.0077	-0.0455	-0.0029	0.0491	0.1185	692.7	-0.0010	-0.0467	-0.0067	0.0383	0.0999
EP ratio	1131.1	0.0270	0.0148	0.0425	0.0649	0.0860	692.7	0.0269	0.0168	0.0431	0.0644	0.0907
SUE	1131.1	0.1190	-0.5929	0.0832	0.7750	1.2068	692.7	0.1231	-0.5759	0.0922	0.7858	1.1828
volume	1131.1	0.6292	0.4539	0.6637	0.8330	0.2447	692.7	0.6521	0.4851	0.6915	0.8493	0.2365
Market cap	1131.1	6978.5	472.1	1319.5	4088.5	23842.6	692.7	10356.9	786.7	2231.4	6846.3	30347.2
Inst. ownership	1131.1	0.6747	0.5652	0.7100	0.8159	0.1881	692.7	0.7151	0.6248	0.7449	0.8364	0.1665
REC	1131.1	3.7374	3.3671	3.7490	4.1049	0.5561	692.7	3.6433	3.1233	3.6623	4.0876	0.6834
ΔREC	1131.1	-0.0797	-0.5205	-0.0780	0.3532	0.7122	692.7	-0.0591	-0.6410	-0.0665	0.5051	0.9085
No. analyst broker	229.3	15.4	2.4	6.1	15.7	26.2	188.3	12.3	1.8	5.3	13.5	18.8
No. industry broker	229.3	13.3	2.9	9.3	20.3	12.4	188.3	10.5	2.3	6.6	15.5	10.5
No. firm broker	229.3	93.6	9.7	29.9	97.4	160.0	188.3	48.2	5.5	17.5	51.8	79.9
No. firm	2765.3	7.4	3.2	6.2	10.1	6.6	1886.7	4.4	2.0	3.4	5.9	3.8
No. industry	2765.3	2.6	1.1	2.2	3.3	1.8	1886.7	1.9	1.0	1.4	2.2	1.3

Table 1.1 Continued

variable	N	Mean	P25	P50	P75	St. dev	N	Mean	P25	P50	P75	St. dev
	Panel C Target price full sample						Panel D Target price restricted sample					
Aggregate score	972.1	0.8687	-1.4242	0.9621	3.4091	3.6180	882.1	1.0109	-1.2417	1.1167	3.5333	3.5105
Aggregate score rank	972.1	-0.1538	-1.1667	-0.0833	1.0000	1.3697	882.1	-0.1174	-1.1000	-0.0500	1.0167	1.3563
BM rank	972.1	-0.6825	-1.9545	-1.0152	0.0606	1.2037	882.1	-0.6577	-1.9500	-1.0000	0.0667	1.2032
Mom rank	972.1	-0.0435	-1.0606	0.0000	1.0303	1.3825	882.1	-0.0688	-1.0500	0.0000	1.0000	1.3574
GP rank	972.1	0.5418	-0.1061	0.7424	1.0455	1.0750	882.1	0.5596	0.0167	0.7333	1.0833	1.0565
IVA rank	820.5	-0.0875	-1.0000	0.0152	1.0152	1.3560	742.1	-0.0585	-1.0000	0.0000	1.0167	1.3499
NOA rank	953.7	-0.4388	-1.6591	-0.7803	0.4242	1.2490	867.5	-0.4371	-1.4333	-0.7583	0.3333	1.2346
OSC rank	972.1	0.7318	0.0000	1.0152	2.0000	1.1534	882.1	0.7504	0.0000	1.0167	2.0000	1.1357
UMO rank	902.1	0.8941	-0.0303	1.6667	2.0000	1.3449	813.7	0.9874	0.0000	1.9333	2.0000	1.3061
Dividend yield	970.2	0.0078	0.0000	0.0002	0.0113	0.0140	880.7	0.0081	0.0000	0.0002	0.0121	0.0141
Idio. volatility	972.1	0.0233	0.0157	0.0213	0.0287	0.0102	882.1	0.0213	0.0145	0.0195	0.0260	0.0092
illiquidity	972.1	0.0155	0.0005	0.0021	0.0080	0.0549	882.1	0.0095	0.0004	0.0014	0.0054	0.0302
Volume	972.1	0.6599	0.4988	0.7009	0.8540	0.2342	882.1	0.6585	0.4986	0.7004	0.8519	0.2345
Market Cap	972.1	7356.5	638.2	1619.5	5011.3	19136.5	882.1	7960.0	722.7	1813.3	5345.5	20521.6
52weekhigh dummy	972.1	0.2732	0.0000	0.1061	0.5455	0.4039	882.1	0.2771	0.0000	0.1167	0.5500	0.4015
Inst. ownership	894.8	0.7180	0.6220	0.7544	0.8501	0.1773	803.2	0.7420	0.6545	0.7776	0.8637	0.1660
External Financing	971.9	0.0159	-0.0603	-0.0045	0.0485	0.1534	881.9	0.0002	-0.0655	-0.0128	0.0334	0.1364
FY1_bias	969.6	0.0040	-0.0033	0.0001	0.0056	0.0229	879.9	0.0034	-0.0033	-0.0001	0.0051	0.0213
LTGREV (%)	972.1	1.1001	-0.9885	0.2743	3.0578	6.6714	882.1	1.0068	-1.0136	0.3001	2.9113	6.4655
IRET	972.1	0.2395	0.1366	0.2059	0.3070	0.1678	882.0	0.2163	0.1145	0.1858	0.2823	0.1843
No. analyst broker	232.1	17.1	2.2	6.4	17.3	29.3	186.2	12.7	1.7	5.1	13.7	19.9
No. industry broker	232.1	12.0	2.2	6.8	18.6	12.5	186.2	10.7	2.0	5.8	15.9	11.5
No. firm broker	232.1	110.3	7.1	26.0	100.5	210.4	186.2	78.0	5.6	19.0	71.3	146.7
No. firm	2807.1	9.1	3.6	7.9	13.0	7.0	1863.8	7.5	3.1	6.4	10.7	5.7
No. industry	2807.1	2.5	1.0	2.0	3.3	1.9	1863.8	2.2	1.0	1.8	2.8	1.6

Table 1.2 Univariate Tests

This table reports the time series average of portfolio characteristics for each aggregate score rank. Full sample includes all the available observations while the restricted sample requires the same analyst to cover the same stock over the 12 months prior to quarter q-6 and quarter q. Top quintile portfolio (long leg) has a value of 2 of *Aggregate score rank (Agg. Score Rank)*. No. stock is the average number of stocks in each quintile portfolio over time. *REC* is the average of consensus recommendations across stocks in each quintile each quarter. Δ*REC* is the average of change in consensus recommendations over prior six quarters across stocks in each quintile portfolio. *Score* is the average of aggregate anomaly scores across stocks in each quintile portfolio. *IRET* is the average consensus implied return of each aggregate score quintile. Long – Short is the difference in the variable (i.e., *REC*, Δ*REC* or *IRET*) between the top quintile (*Agg. Score Rank*=2) and bottom quintile (*Agg. Score Rank* =-2). Time series t statistics (Newey West adjusted with four lags) are in the parentheses.

Panel A Recommendation Sample

	Full				Restricted			
Agg. Score Rank	No. stock	score	REC	ΔREC	No. stock	score	REC	ΔREC
(short) -2	367.6	-4.3564	3.7678	-0.1704	189.6	-4.2038	3.6470	-0.1537
-1	353.5	-0.7209	3.7347	-0.1153	199.9	-0.6953	3.6259	-0.1042
0	369.3	1.4521	3.7232	-0.0788	224.0	1.4479	3.6224	-0.0631
1	331.3	3.4306	3.7341	-0.0242	202.9	3.4253	3.6313	-0.0153
(Long) 2	308.2	6.1646	3.7594	0.0561	179.3	6.1307	3.6389	0.0452
Long - Short			-0.0084	0.2723			-0.0081	0.1989
			(-0.45)	(9.82)			(-0.45)	(7.18)

Panel B Target Price Sample

	Full			Restricted		
Agg. Score Rank	No. stock	score	iret	No. stock	score	iret
(short) -2	399.7	-4.3008	0.3336	311.8	-4.1563	0.3032
-1	352.9	-0.6452	0.2648	291.5	-0.6161	0.2345
0	374.3	1.4785	0.2437	332.7	1.4785	0.2141
1	341.4	3.4352	0.2329	292.0	3.4296	0.2038
(Long) 2	307.4	6.1596	0.2378	253.3	6.1333	0.2052
Long - Short			-0.0958			-0.098
			(-6.32)			(-6.71)

Table 1.3 Conditional Univariate Test

Table 1.3 reports univariate test conditional on analyst-stock level recommendation between 1999 and 2016. Each quarter, we collect the most recent recommendation and target price by an analyst for a stock over the prior 12 months. Conditional on the recommendation received, we show the average implied return (*IRET*) of stocks in each aggregate score rank. No. stock is the time series average of number of stocks in each aggregate score rank each quarter. No. quarters is the number of quarters with available data between 1999 and 2016. Mean, median and std. dev are the time series mean, median and standard deviation of quarterly implied return of each aggregate score rank conditional on the value of stock recommendation.

Analysis Variable : average IRET						
Recommendation	Aggregate Score rank	No. Quarters	Mean	Median	Std. Dev	No. Stock
5 (strong buy)	(short leg) -2	71	0.4205	0.3693	0.1243	403.7
	-1	71	0.3492	0.3141	0.0927	325.7
	0	71	0.3200	0.2970	0.0690	340.8
	1	71	0.3075	0.2909	0.0657	301.1
	(long leg) 2	71	0.3035	0.2876	0.0604	263.5
4	(short leg) -2	71	0.3844	0.3397	0.1211	529.4
	-1	71	0.3100	0.2825	0.0789	443.7
	0	71	0.2848	0.2701	0.0683	451.6
	1	71	0.2674	0.2618	0.0429	391.4
	(long leg) 2	71	0.2675	0.2569	0.0433	324.4
3	(short leg) -2	71	0.1827	0.1188	0.1252	571.2
	-1	71	0.1355	0.1019	0.0775	511.4
	0	71	0.1228	0.0962	0.0675	550.6
	1	71	0.1187	0.0914	0.0692	470.5
	(long leg) 2	71	0.1170	0.0932	0.0615	386.5
2	(short leg) -2	71	-0.0116	-0.0812	0.1724	70.0
	-1	71	-0.0248	-0.0722	0.1701	63.3
	0	71	-0.0676	-0.0799	0.0798	68.7
	1	70	-0.0252	-0.0825	0.1410	57.4
	(long leg) 2	70	0.0185	-0.0957	0.4415	48.1
1 (strong sell)	(short leg) -2	68	-0.1650	-0.2051	0.1560	25.1
	-1	69	-0.1600	-0.1829	0.1333	19.2
	0	68	-0.1484	-0.1555	0.1064	23.5
	1	69	-0.1504	-0.1648	0.1118	18.3
	(long leg) 2	66	-0.1555	-0.1624	0.1081	17.0

Table 1.4 Impact of Aggregate Score Rank on Consensus Recommendation and Its Revision

This table presents the Tobit regression model where the dependent variable, consensus stock recommendation (*REC*) or change in consensus recommendations from quarter t-6 to quarter t (Δ*REC*) is regressed on stock's aggregate score rank and control variables. Quarter dummies are included in each regression and standard errors are clustered at firm and quarter level. Dependent variables in column (1) to (3) are consensus stock recommendations (*REC*). Dependent variables in column (4) to (6) are change in consensus recommendation over quarter q-6 and quarter q (Δ*REC*). Column (1) and (4) include all stocks in the sample. Column (2) and (5) include stocks in the top two aggregate score ranks. Column (3) and (6) include stocks in the bottom two aggregate score ranks. *Aggregate score rank* is each stock's aggregate score rank each quarter. *SUE* is standardized unexpected earnings. *SG* is revenue in the past four quarters over the revenues in the 4 prior quarters. *TA* is total accrual over total assets. *Volume* is the percentile based on average daily stock trading volume over shares outstanding over past 6 months in the stock exchange where the stock is listed. *Size* is natural log of stock market capitalization (in thousands dollars). *SUE* is standardized unexpected earnings. *EP* is earnings-to-price. *Inst. own* is institutional ownership.

Panel A recommendation (Full sample)						
	(1)	(2)	(3)	(4)	(5)	(6)
	REC	REC	REC	ΔREC	ΔREC	ΔREC
	Full	Long	Short	Full	Long	Short
Aggregate score rank	0.010***	0.033***	-0.012	0.061***	0.071***	0.057***
	(3.33)	(3.55)	(-1.60)	(16.26)	(6.33)	(5.97)
SG	0.279***	0.380***	0.235***	0.098***	0.136***	0.090***
	(16.53)	(14.13)	(14.64)	(8.74)	(4.84)	(7.23)
TA	0.316***	0.309***	0.286***	0.176***	0.160***	0.199***
	(13.00)	(7.47)	(9.13)	(5.73)	(3.19)	(4.91)
SUE	0.058***	0.044***	0.066***	0.060***	0.045***	0.065***
	(20.32)	(11.97)	(16.98)	(16.23)	(9.26)	(14.69)
Volume	-0.020	0.008	-0.071***	-0.093***	-0.023	-0.160***
	(-0.90)	(0.27)	(-2.84)	(-5.25)	(-0.85)	(-6.69)
Inst. ownership	0.215***	0.157***	0.240***	0.184***	0.078**	0.204***
	(7.70)	(3.81)	(8.00)	(6.86)	(2.27)	(5.93)
size	-0.012***	-0.017***	-0.001	0.026***	0.004**	0.050***
	(-4.49)	(-4.77)	(-0.48)	(7.41)	(2.16)	(22.22)
EP	0.263***	0.193***	0.285***	-0.083	-0.185**	-0.056
	(6.77)	(2.81)	(6.24)	(-1.42)	(-2.13)	(-0.79)
Quarter dummies	Y	Y	Y	Y	Y	Y
No. observation	85325	29796	36783	85325	29796	36783
Pseudo R square	0.110	0.102	0.124	0.041	0.030	0.046

Table 1.4 Continued

Panel B Recommendation (Restricted Sample)						
	(1)	(2)	(3)	(4)	(5)	(6)
	REC	REC	REC	ΔREC	ΔREC	ΔREC
	Full	Long	Short	Full	Long	Short
Aggregate Score rank	0.008**	0.024*	-0.005	0.046***	0.049***	0.047***
	(2.01)	(1.80)	(-0.39)	(10.16)	(3.23)	(2.86)
SG	0.325***	0.396***	0.287***	0.114***	0.123**	0.124***
	(13.55)	(9.95)	(9.99)	(4.11)	(2.27)	(3.66)
TA	0.264***	0.305***	0.233***	0.169***	0.188**	0.193**
	(5.73)	(4.50)	(3.70)	(2.87)	(2.13)	(2.48)
SUE	0.049***	0.036***	0.054***	0.055***	0.039***	0.059***
	(12.69)	(6.63)	(9.55)	(10.84)	(5.53)	(8.07)
Volume	-0.025	-0.048	-0.054	-0.090***	-0.066	-0.114***
	(-0.85)	(-1.19)	(-1.47)	(-3.54)	(-1.64)	(-2.83)
Inst. ownership	0.273***	0.284***	0.295***	0.140***	0.159***	0.119**
	(6.84)	(4.56)	(6.05)	(3.75)	(3.12)	(2.25)
size	0.014***	0.009**	0.026***	0.016***	0.003	0.033***
	(4.32)	(2.02)	(6.37)	(3.86)	(1.34)	(10.95)
EP	0.181***	0.008	0.244***	-0.066	-0.263**	0.026
	(3.98)	(0.10)	(4.30)	(-1.11)	(-2.33)	(0.33)
Quarters dummies	Y	Y	Y	Y	Y	Y
No. observations	51171	18865	20536	51171	18865	20536
Pseudo R square	0.045	0.041	0.055	0.017	0.015	0.018

Table 1.5 Impact of Aggregate Score Rank on Consensus Implied Return

This table presents the OLS regression model where the dependent variable, consensus implied return (*iret*) is regressed on stock's *Aggregate Score rank* and control variables. Quarter fixed effects are included in each regression and standard errors are clustered at firm and quarter level. Each quarter we collect the most recent price target estimates by an analyst over the prior 12 months for a stock and compute the implied return for the stock by each analyst. Implied return is analyst target price/the prior day stock price -1. Both target prices and stock prices are manually split adjusted. Column (1) to (3) include all stocks in the sample. Column (4) to (6) are generated with restricted sample, which requires an analyst to cover the same stock in the 12 months prior to quarter t-6 and quarter t. Column (2) and (5) include stocks in the top two aggregate score ranks. Column (4) and (6) include stocks in the bottom two aggregate score ranks. *Dividend yield* is calculated as the dividend payment of the prior year, divided by the market value of common equity at the end of the prior fiscal year. *SUE* is standardized unexpected earnings. *Volume* is the percentile based on average daily stock trading volume over shares outstanding over past 6 months in the listed stock exchange. *Size* is natural log of stock market capitalization (in thousands dollars). *LTGREV* is change in analysts' consensus long term growth forecast. *FY1_bias* is the difference between analysts' consensus one-year ahead EPS forecasts and the corresponding actual EPS, scaled by stock prices when the consensus target prices are computed. *External financing* is the amount of external financing scaled by the average total assets.

	(1)	(2)	(3)	(4)	(5)	(6)
	IRET	IRET	IRET	IRET	IRET	IRET
	Full sample			Restricted sample		
	All	Long	Short	All	Long	Short
Agg. score rank	-0.013***	-0.007**	-0.030***	-0.013***	-0.008**	-0.031***
	(-8.06)	(-2.31)	(-7.02)	(-8.19)	(-2.15)	(-6.30)
Inst. ownership	-0.072***	-0.056***	-0.077***	-0.039***	-0.028*	-0.043**
	(-4.77)	(-3.11)	(-4.12)	(-2.59)	(-1.66)	(-1.98)
52weekhigh dummy	-0.020***	-0.017***	-0.026***	-0.016***	-0.013***	-0.021***
	(-5.75)	(-4.77)	(-5.45)	(-5.81)	(-4.07)	(-5.28)
size	-0.013***	-0.014***	-0.014***	-0.006***	-0.007***	-0.008***
	(-7.63)	(-7.09)	(-6.86)	(-3.97)	(-3.63)	(-3.82)
Dividend yield	-0.600***	-0.375**	-0.719***	-0.813***	-0.537***	-1.006***
	(-4.94)	(-2.08)	(-4.83)	(-6.16)	(-2.93)	(-6.14)
Idio. volatility	4.608***	3.910***	4.794***	4.543***	3.810***	4.774***
	(10.00)	(8.56)	(8.98)	(7.64)	(7.28)	(6.82)
Illiquidity	0.136***	0.147***	0.117**	0.273***	0.360***	0.171
	(3.75)	(3.43)	(2.08)	(4.64)	(6.14)	(1.43)
volume	0.003	-0.006	0.005	0.006	-0.005	0.009
	(0.25)	(-0.40)	(0.40)	(0.54)	(-0.41)	(0.67)
External Financing	0.073***	0.036**	0.089***	0.077***	0.051***	0.086***
	(6.74)	(2.52)	(6.34)	(6.32)	(3.85)	(4.29)
FY1_bias	0.186***	0.279**	0.120	0.093	0.220*	0.020
	(3.05)	(2.36)	(1.63)	(1.26)	(1.68)	(0.20)
LTGREV	0.001***	0.000	0.001***	0.001***	0.000	0.001***
	(3.87)	(0.79)	(3.50)	(3.48)	(0.73)	(3.26)
Quarter fixed effects	Y	Y	Y	Y	Y	Y
No. observations	58743	20191	25616	48001	16917	20174
Adjusted R-square	0.336	0.263	0.365	0.212	0.161	0.233

Table 1.6 Brokerage Firms' Academic Sophistication Persistence (Recommendation Sample)

This table shows the persistence of brokerage firms' academic sophistication (e.g., whether the broker's recommendations are consistent or contrary to anomaly prescription). Each quarter, stock-analyst level recommendation (*REC*) is regressed on stock aggregate score rank (*Aggregate Score rank*), brokerage fixed effect, interaction term (*brokerage fixed effect* × *Aggregate Score rank*) and control variables. Brokerage firms are then sorted into quartiles based on their interaction coefficients each quarter. This table reports the average of interaction coefficient across brokerage firms in each quartile portfolio in the formation quarter and subsequent four quarters. We also report the average quartile rank of brokerage firms in each quartile and the retention ratio, which is the percentage of brokerage firms that stay in the same quartile over the subsequent four quarters. No. brokerage firm is the average number of brokerage firms in each quartile each quarter. Brokerage firms need to cover more than 10 stocks to be included in the sample.

		Quarter			
Current Quarter	Portfolio Formation quarter	Q+1	Q+2	Q+3	Q+4
Consistency Quartiles					
Q1 Interaction coefficient	-0.2707	-0.1311	-0.0467	-0.0159	-0.0029
Coefficient t stat	-10.04	-4.90	-1.80	-0.59	-0.11
Retention ratio	100.00%	54.61%	41.18%	35.26%	31.46%
Quartile rank	1.0	1.8	2.2	2.3	2.4
No. brokerage firms	26.6	24.7	23.6	22.7	21.9
Q2 Interaction coefficient	-0.0385	-0.0210	-0.0137	-0.0133	-0.0071
Coefficient t stat	-1.66	-0.88	-0.58	-0.55	-0.29
Retention ratio	100.00%	40.86%	36.06%	33.30%	33.95%
Quartile rank	2.0	2.3	2.4	2.4	2.5
No. brokerage firms	27.1	26.5	25.8	25.2	24.6
Q3 Interaction coefficient	0.0390	0.0151	0.0048	0.0063	0.0115
Coefficient t stat	1.69	0.63	0.19	0.26	0.46
Retention ratio	100.00%	39.28%	34.36%	32.10%	30.89%
Quartile rank	3.0	2.7	2.6	2.6	2.6
No. brokerage firms	27.5	26.7	26.1	25.6	25.1
Q4 Interaction coefficient	0.2970	0.1580	0.0677	0.0233	-0.0192
Coefficient t stat	12.09	5.97	2.51	0.85	-0.69
Retention ratio	100.00%	53.96%	41.49%	34.25%	31.10%
Quartile rank	4.0	3.2	2.9	2.7	2.6
No. brokerage firms	26.9	25.0	23.9	22.8	21.9
Q4-Q1 (interaction coeff.)	0.5678	0.2891	0.1144	0.0392	-0.0163
t stat	34.66	17.04	8.02	2.37	-0.92

Table 1.7 Brokerage Firms' Academic Sophistication Persistence (Target Price Sample)

This table shows the persistence of brokerage firms' academic sophistication (e.g., whether the target price estimates from a broker are consistent or contrary to anomaly prescription). Each quarter, each analyst' implied return (*iret*) is regressed on stock's *Aggregate Score rank*, brokerage fixed effect, the interaction term (*brokerage fixed effect* × *Aggregate Score rank*) and control variables. *Iret* in quarter t by analyst i for stock j is calculated using the most recent target price by analyst i for stock j over the prior 12 months to quarter t. Brokerage firms are sorted into quartiles based on the coefficient of the interaction terms each quarter. We report the average quartile interaction coefficient in the formation quarter and subsequent four quarters. We also report the average quartile rank of brokerage firms in each quartile and the retention ratio, which is the percentage of brokerage firms that are in the same quartile over the subsequent four quarters. No. brokerage firm is the average number of brokerage firms in each quartile each quarter. Brokerage firms need to cover more than 5 stocks to be included in the sample.

		Quarter			
Current Quarter	Portfolio Formation quarter	Q+1	Q+2	Q+3	Q+4
Consistency Quartiles					
Q1 Interaction coefficient	-0.0788	-0.0372	-0.0224	-0.0131	-0.0137
Coefficient t stat	-9.88	-5.68	-3.37	-1.99	-1.84
Retention ratio	100.00%	49.64%	40.15%	32.32%	30.82%
Quartile rank	1.00	1.90	2.18	2.37	2.41
No. brokerage firms	27.5	25.1	24.0	22.5	21.8
Q2 Interaction coefficient	-0.0200	-0.0138	-0.0107	-0.0084	-0.0073
Coefficient t stat	-3.04	-2.10	-1.62	-1.25	-1.10
Retention ratio	100.00%	40.08%	35.73%	32.14%	32.25%
Quartile rank	2.00	2.30	2.41	2.45	2.47
No. brokerage firms	27.9	27.2	26.7	26.0	25.6
Q3 Interaction coefficient	0.0005	-0.0028	-0.0043	-0.0050	-0.0062
Coefficient t stat	0.07	-0.43	-0.64	-0.73	-0.90
Retention ratio	100.00%	40.82%	35.02%	32.74%	33.33%
Quartile rank	3.00	2.70	2.62	2.58	2.54
No. brokerage firms	28.4	27.8	27.3	26.6	26.0
Q4 Interaction coefficient	0.0523	0.0189	0.0066	-0.0009	-0.0029
Coefficient t stat	7.92	2.73	0.93	-0.13	-0.42
Retention ratio	100.00%	51.58%	39.58%	33.43%	29.83%
Quartile rank	4.00	3.12	2.81	2.66	2.59
No. brokerage firms	27.6	25.2	23.8	22.7	21.4
Q4-Q1 (interaction coeff.)	0.1311	0.0562	0.0270	0.0122	0.0102
t stat	20.01	15.85	8.47	3.72	3.73

Table 1.8 Performance of Brokerage Firms' Recommendation and Target Prices

This table reports the Fama French monthly alpha of strategies following recommendations (Panel A) and target prices (Panel B) issued by academically sophisticated and non-academically sophisticated brokerage firms. At the end of quarter q, brokerage firms are sorted into quartiles based on the coefficients of the interaction term between stock's aggregate score rank and brokerage firm fixed effects from regression (5) or (6). Top quartile brokerages firms are labeled as academically sophisticated and bottom quartile brokerage firms are labeled as non-sophisticated. In the subsequent quarter q+1, for each stock we compute the average recommendation (implied return) issued by (non) sophisticated brokerage firms and sort those stocks into terciles based on their average recommendation (implied return) value. Stocks with average recommendation (implied return) levels in the top tercile are labeled buy and stocks in the bottom tercile are labeled by sell. We calculate monthly value weighted stock return of each tercile in quarter q+2 using stock market capitalization at the end of quarter q+1. In each panel within each tercile, the first row shows the Fama French monthly alpha, the second row shows the t statistics in the parentheses and the third row shows the average number of stocks in each tercile each month. Brokerage firms need to cover more than 10 stocks in the recommendation sample and more than 5 stocks in the target price sample.

			(1)	(2)	(1)-(2)
			Sophisticated brokerages	Non-sophisticated brokerages	Diff
	Panel A FF monthly alpha of following stock recommendations				
	Average recommendation tercile				
Sell	Alpha	1	-0.0004	0.0016	-0.0020
	t-stat		(-0.31)	(1.55)	(-1.34)
	No. stocks		248.1	266.5	
		2	0.0017	-0.0006	0.0023
			(1.41)	(-0.62)	(1.52)
			197.7	219.3	
Buy		3	0.0010	-0.0018	0.0028
			(0.88)	(-1.67)	(1.72)
			221.9	234.1	
Buy - Sell			0.0014	-0.0033	0.0047
			(0.76)	(-2.19)	(1.98)
	Panel B FF monthly alpha of following implied returns (derived from target prices)				
	Average implied return tercile				
Sell		1	0.0001	-0.0005	0.0006
			(0.11)	(-0.49)	(0.43)
			292.3	296.3	
		2	-0.0010	-0.0019	0.0009
			(-0.80)	(-1.56)	(0.62)
			307.6	311.4	
Buy		3	-0.0050	-0.0054	0.0004
			(-2.81)	(-2.50)	(0.21)
			306.3	312.5	
Buy - Sell			-0.0051	-0.0049	-0.0002
			(-2.60)	(-1.99)	(-0.07)

Table 1.9 Institutional Investor's All-Star Analysts and Analysts' Experience

This table examines whether star analysts and analysts' experiences are associated with academic sophistication. We run Fama Macbeth regression and adjust standard errors in Newey West procedure with 4 quarter lags in this test. Panel A reports the time series average coefficients of each independent variable from Tobit regression $rec = \alpha + \beta_1 Aggregate\ score\ rank + \beta_2 Star + \beta_3 Aggregate\ score\ rank \times Star + \beta_4 Analyst'special\ experience + +\beta_5 Aggregate\ score\ rank \times Analyst'special\ experience + controls$. Panel B reports the time series mean of each coefficients from the OLS regression $iret = \alpha + \beta_1 Aggregate\ score\ rank + \beta_2 Star + \beta_3 Star \times Aggregate\ score\ rank + \beta_4 Analyst's\ general\ experience + \beta_5 Aggregate\ score\ rank \times Analyst's\ general\ experience + controls$ over all the quarters in the sample period. *Aggregate Score rank* is the aggregate score rank for each stock. *Star* is a dummy variable which equals 1 if the analyst who issues the recommendation (or target price) is among the top three research teams by *Institutional Investor* magazine.

Panel A FM-Tobit regression in recommendation sample			
	Coefficient	t-Value	P-value
Aggregate score rank	0.0020	0.49	0.6283
Star analyst dummy	-0.1142***	-7.99	<.0001
Aggregate score rank × Star analyst dummy	-0.0164***	-2.94	0.0052
Analyst special experience	-0.0018	-1.02	0.3138
Aggregate score rank × Analyst special experience	0.0018***	3.16	0.0028
Earnings-to-price ratio	0.2800***	3.59	0.0008
Sales growth	0.3281***	12.57	<.0001
Total accruals/total assets	0.1742***	4.08	0.0002
Institutional ownership	0.1532***	5.90	<.0001
Size	0.0018	0.55	0.582
SUE	0.0428***	9.94	<.0001
Volume	-0.1884***	-8.20	<.0001
Top brokerage dummy	-0.1590***	-8.03	<.0001

Panel B FM-OLS regression in target price sample			
	Coefficient	t-Value	P-value
Aggregate score rank	-0.0108***	-4.15	0.000
Star analyst dummy	-0.0164***	-9.27	0.000
Aggregate score rank × Star analyst dummy	0.0016	1.32	0.192
Analyst general experience	0.0011***	5.04	0.000
Aggregate score rank × Analyst general experience	0.0004*	1.76	0.086
52 week high dummy	-0.0187***	-5.99	0.000
Dividend yield	-0.5125***	-5.59	0.000
External Financing	0.0840***	8.94	0.000
Idiosyncratic volatility	2.1951***	6.84	0.000
Illiquidity	0.2236*	1.91	0.062
Inst. ownership	-0.0289***	-4.35	0.000
Top brokerage dummy	-0.0423***	-8.92	0.000
Volume	0.0114	1.37	0.178

Table 1.10 Quintile Anomaly Portfolio Quarterly Alphas in the Subsequent 12 Months

This table shows the quarterly three factor alphas of calendar time (quintile) anomaly portfolio formed each quarter. The quintile rank value is from -2 to 2, where 2 indicates long leg and -2 indicates short leg. UMO means “undervalued minus overvalued”, where undervalued portfolio (the portfolio investors should long) includes firms with equity/debt repurchases and no equity/debt issuances over the prior two fiscal years. Overvalued portfolio (the portfolio investors should short) includes firms with equity/debt repurchases but no issuances over the prior two fiscal years. Neutral portfolio contains the rest firms. Stocks in the undervalued portfolio receive value 2 for umo_rank, stocks in the overvalued portfolio receive value -2 for umo_rank and stocks in the neutral portfolio receive value 0 for umo_rank. Annual anomaly portfolios are formed each June and the table shows the average quarterly return in the subsequent 12 months. For the top quintile momentum and aggregate anomaly score portfolios, in calendar quarter t, we equal weigh the quarterly return of the top quintiles formed in calendar quarter t-1, t-2, t-3 and t-4. Moving to calendar quarter t+1, we drop the top quintile formed in calendar quarter t-4 and add the top quintile formed in calendar t. Utilities, financial stocks as well as stock with price less than $5 are excluded from the computation. In panel A, returns of stocks in each quintile are value weighted based on the market capitalization at the formation date and the weights are remained during the holding period. For BM anomaly, three factor alphas are generated without HML as an independent variable. The sample period is from 1982 to 2016.

	Quintile Rank	NOA	GP	IVA	OSC	B/M*	MOM	UMO*	Agg. anomaly score
Panel A Value weighted quarterly three factor alphas (%) in 4 quarters holding period									
Short	-2	-1.05	-1.65	-0.83	-1.51	-0.30	-0.70	-0.68	-1.65
	-1	-0.18	-0.85	0.01	-0.20	0.18	0.03	--	-0.11
	0	0.21	0.07	0.41	-0.00	0.50	0.08	-0.01	0.12
	1	0.57	0.32	0.38	0.10	0.38	0.20	--	0.45
Long	2	0.75	0.77	0.45	0.34	0.87	0.38	0.46	0.84
Long-short		1.80	2.42	1.28	1.86	1.17	1.06	1.14	2.49
		(3.7)	(3.6)	(3.0)	(3.8)	(1.8)	(1.5)	(3.3)	(6.1)
Panel B Equal weighted quarterly three factor alphas (%) in 4 quarters holding period									
Short	-2	-1.37	-1.54	-1.67	-1.20	-1.30	-1.00	-1.45	-2.07
	-1	0.08	-1.16	-0.22	-0.39	0.07	-0.06	--	-0.21
	0	0.42	-0.15	0.42	-0.01	0.63	0.32	-0.34	0.30
	1	0.44	0.32	0.63	0.14	0.73	0.47	--	0.73
Long	2	0.48	0.76	0.49	0.24	1.05	0.09	0.48	1.07
Long-short		1.86	2.30	2.15	1.44	2.35	1.09	1.93	3.12
		(4.0)	(3.8)	(6.2)	(3.8)	(3.8)	(1.7)	(5.4)	(7.3)

Table 1.11 Replication of Table 2 in Edelen et al. (2016)

Following method in Edelen et al. (2016), each June in year t we form anomaly portfolios based on the anomaly characteristics (i.e., NOA, IVA, GP, BM, OSC, UMO) into terciles and compute the monthly portfolio excess return and Fama French alpha (for BM portfolio the alpha is generated in regression where independent variables are SMB and market excess return) in the subsequent 12 months (holding period of annual updated anomalies are 12 months, which is different from the holding period for momentum). Momentum portfolios are formed at the end of each calendar quarter with a holding period of three months skipping one month after formation. The long portfolios include stocks in the top 30% outperforming tails and the short portfolio include stocks in the top 30% underperforming tails. Portfolio AVG takes an equal position across the seven anomalies (we equal weight the monthly portfolio return across the six individual anomalies and run time series Fama French three factor regression to generate alpha). Heteroskedasticity-adjusted t-statistics are in parentheses. Utilities, financial and stocks with price less than $5 are excluded. Returns in each portfolio during holding period are value weighted based on the market capitalization of component stocks at the formation date. The sample period is from 1982 to 2012.

	NOA	GP	IVA	OSC	B/M	MOM	UMO	AVG
	Panel A: monthly excess return (%)							
Long leg	0.86	0.88	0.88	0.73	0.93	0.94	0.89	0.87
Short leg	0.43	0.35	0.36	0.62	0.56	0.47	0.28	0.43
Long - short	0.43	0.53	0.52	0.10	0.37	0.47	0.61	0.44
	(3.7)	(3.6)	(4.2)	(0.7)	(2.1)	(3.3)	(3.9)	(5.2)
	Panel B: monthly three factor alphas (%)							
Long leg	0.14	0.22	0.15	0.04	0.22	0.27	0.15	0.13
Short leg	-0.37	-0.54	-0.42	-0.28	-0.24	-0.41	-0.50	-0.38
Long - short	0.50	0.76	0.57	0.32	0.46	0.68	0.65	0.50
	(4.4)	(5.6)	(5.4)	(2.4)	(2.7)	(5.1)	(5.7)	(6.8)

Table 1.12 Variable Definitions

Variable	Definition
Net operating asset rank	*Net operating asset* (NOA) is calculated as the sum of short-term debt (DLC), long-term debt (DLTT), minority interest (MIB), preferred stock (PSTK), and common equity (CEQ) minus cash and short-term investment (CHE), deflated by lagged total assets (AT).*Net operating asset rank* is the quintile anomaly rank based on stocks' net operating assets value, and value is between -2 and 2. -2 represents short leg and 2 represents long leg
Investment-to-asset rank	*Investment-to-Assets* (IVA) is calculated as the change in gross property, plant, and equipment (PPEGT) plus the change in inventories (INVT), deflated by the lagged total assets (AT). *Investment-to-asset rank* is the quintile anomaly rank based on stocks' investment to asset value, and value is between -2 and 2. -2 represents short leg and 2 represents long leg
Gross profitability rank	*Gross Profitability* (GP) is calculated as the total revenues (REVT) minus cost of goods sold (COGS), divided by total assets (AT). *Gross profitability rank* is the quintile anomaly rank based on stocks' gross profitability value, and value is between -2 and 2. -2 represents short leg and 2 represents long leg
Ohlson score rank	*Ohlson score* (OSC) is calculated following Ohlson (1980) which uses information of leverage, total assets, total liability, working capital, net income and cash flow from operation. *Ohlson score rank* is the quintile anomaly rank based on stocks' Olson score value, and value is between -2 and 2. -2 represents short leg and 2 represents long leg
Book-to-Market rank	*Book-to-Market ratio* (BM) is calculated as shareholders equity (stockholder equity or total common equity plus preferred stock par value or total assets minus total liabilities and minority interest) minus preferred stock value (using redemption, liquidating or carrying value). *Book-to-market rank* is the quintile anomaly rank based on stocks' book-to-market ratios, and value is between -2 and 2. -2 represents short leg and 2 represents long leg
Momentum rank	*Momentum* (MOM) is calculated using stocks' return in prior 12 month returns. *Momentum rank* is the quintile anomaly rank based on stocks' past 12 month returns, and value is between -2 and 2. -2 represents short leg and 2 represents long leg
Undervalued minus overvalued rank	*Undervalued minus overvalued (UMO)*: the undervalued portfolio includes firms that have equity or debt repurchase and no equity or debt issuances during the two most recent fiscal years and the overvalued portfolio include firms that have either equity or debt issuance but no equity or debt repurchases in the past two most recent fiscal years
aggregate anomaly score	The aggregate anomaly score is the summation of individual quintile anomaly ranks across NOA, IVA, GP, OSC, BM and MOM. By construction, the value of Score is between -12 and 12.

Table 1.12 Continued

Variable	Definition
aggregate score rank	This is the quintile rank based on stock aggregate anomaly score. Value of aggregate score rank is from -2 to 2, with -2 represent the bottom quintile (short leg of anomaly) and 2 represent the top quintile (long leg of anomaly)
52 week high dummy (d_52weekhigh)	a dummy variable which equals one if the average daily stock price over the most recent quarter is above 95% of the highest stock price over the prior 12 months.
Earnings-to-price (EP)	$$\frac{\sum_{i=0}^{3} EPS_{T-i}}{P_T}$$ EP is the rolling sum of EPS for preceding four quarters, deflated by price at the end of quarter T
External financing (Ex_fin)	The amount of external financing scaled by the average total assets $$= \frac{(SSTK - PRSTKC - DV + DLTIS - DLTE + \Delta DLC)}{(total\ asssets + lagged\ total\ assets)}$$
Realized earnings forecast errors (FY1_BIAS)	The difference between analysts' consensus one-year ahead EPS forecasts and the corresponding actual EPS, scaled by stock prices when the consensus target prices are computed
Amihud liquidity (Illiq)	Calculated with the following formula using data over the twelve months preceding the current month $$\frac{1}{D_i}\sum_{t=1}^{D_i}\frac{\lvert r_{it}\rvert}{Dvol_{it}} * 1{,}000{,}000$$ r_{it} is daily returns and $Dvol_{it}$ is daily dollar trading volume (price x volume) for stock i on day t. D_i is the number of days with available ratio over the twelve months measurement window
Institutional ownership (Inst. own)	The quarterly shares owned by institutional investors over the total shares outstanding. Observations with greater than 100% aggregate institutional ownership are coded missing
Sales growth (SG)	$$\frac{\sum_{i=0}^{3} Sales_{T-i}}{\sum_{i=0}^{3} Sales_{T-4-i}}$$ which is the rolling sum of sales for preceding four quarters over the rolling sum of sales for second preceding set of four quarters and T is the most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter q with T >= q-4

Table 1.12 Continued

Variable	Definition
Long term growth revision (LTGREV)	*Change in analysts' consensus long term growth forecast*
Standardized unexpected earnings (SUE)	$$\frac{EPS_T - EPS_{T-4}}{\sigma_T}$$ the nominator is the unexpected earnings for quarter T, with EPS defined as earnings per share (diluted) excluding extraordinary items, adjusted for stock distributions and the denominator is the standard deviation of unexpected earnings over eight preceding quarters (quarter T-7 to quarter T)
Total accrual over total assets (TA)	$$\frac{(\Delta Current\ Assets_T - \Delta Cash_T) - (\Delta Current\ Liabilities_T - \Delta Current\ Long\ term\ debt_T) - \Delta Deferred\ Taxes_T - Depreciation\&Amortization_T}{(Total\ Assets_T + Total\ Assets_{T-4})/2}$$ T is the most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter q with T >= q-4. The timeline in the end of this document show more detail about T
Volume	First calculate the average (daily trading volume over shares outstanding) during the past six months prior to the end of quarter q, then sort the average daily turnover within the stocks' listed exchange (NYSE,AMEX or NASDAQ) into 100 percentiles (i.e., 0 to 99) and then converted the percentile into 0 and 1 by dividing by 99. Volume is between 0 and 1.
Dividend yield (Div_y)	*Calculated as the dividend payment of the prior year, divided by the market value of common equity at the end of the prior fiscal year.*
Idiosyncratic volatility (Idio_vol)	Measured by standard deviation of the residual in Fama French 3 factor regression with three month daily return data

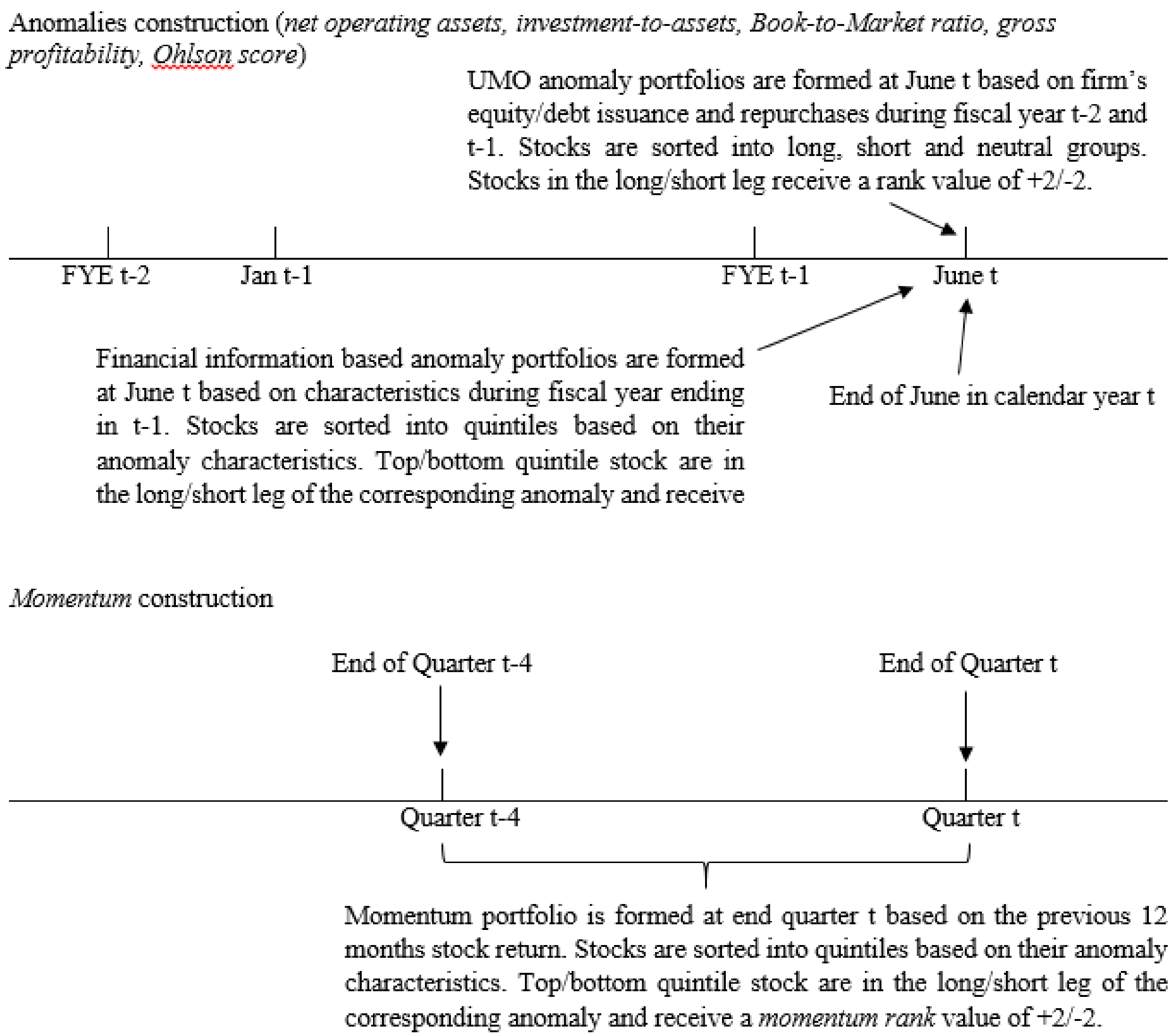
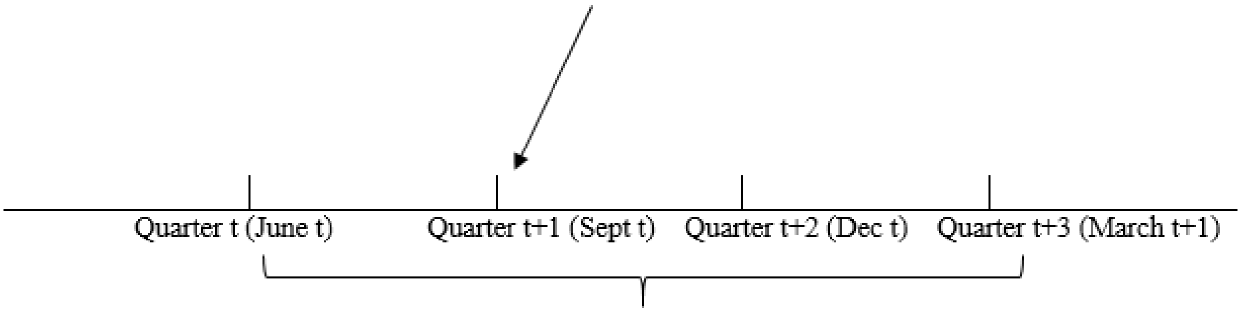


Figure 1.1 Anomaly Constructions

Aggregate anomaly score construction

$$
\begin{aligned}
&Aggregate\ anomaly\ score_{t+1} \\
&= Momentum\ rank_{t+1} + Net\ operating\ asset\ rank_t \\
&+ Investment\ to\ asset\ rank_t + BM\ rank_t \\
&+ gross\ profitability\ rank_t + Ohlson\ score\ rank_t \\
&+ Undervalued\ minus\ overvalued\ score\ rank_t
\end{aligned}
$$



Aggregate anomaly score is the summation of seven individual anomaly ranks. In each quarter between quarter t and quarter t+3, each stock has a *momentum rank* based on prior 12 month returns and other anomaly ranks received in quarter t (June in calendar year t)

Figure 1.2 Aggregate Anomaly Score Constructions

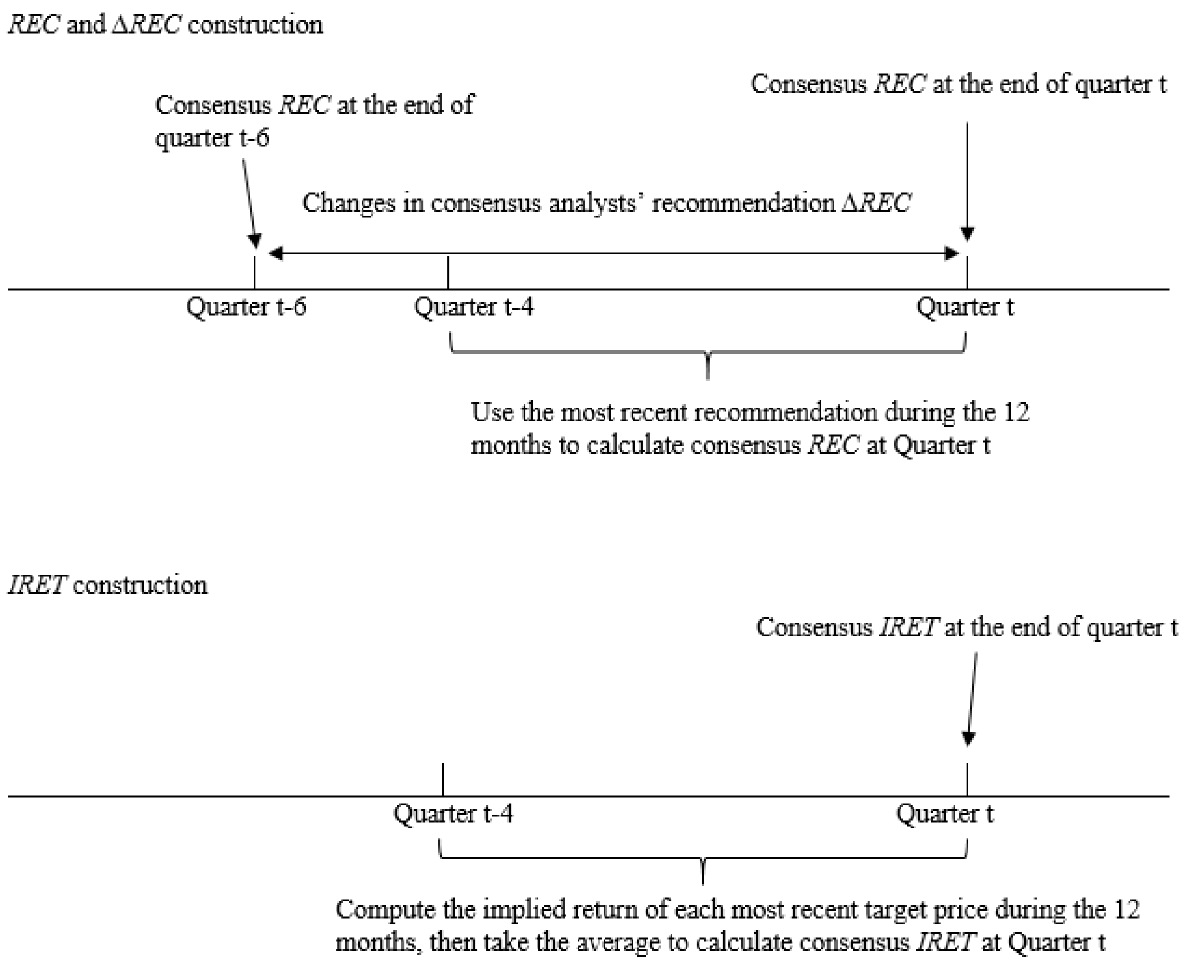


Figure 1.3 Consensus Recommendation and Implied Return Constructions

CHAPTER II
DO HEDGE FUNDS VALUE SELL SIDE ANALYSTS DIFFERENTLY?

Abstract

Being elected as *Institutional Investor's* (II) All-star is an important accolade for sell side analysts. Prior studies have treated II-voted star analysts as a homogenous group. However, there is substantial heterogeneity among institutional investors that comprise the population of voters (i.e., hedge funds vs. traditional long-only asset managers). Due to significantly different investment strategies, we conjecture that hedge funds value different sell side analysts' qualities than other traditional asset managers. Using a novel dataset which identifies the best sell side analysts voted by hedge funds only, we show that hedge funds favored analysts provide more frequent research updates and have better stock picking skills than star analysts favored by non-hedge funds institutional investors.

1. Introduction

Being selected by institutional investor as a star analyst is substantial for sell side analysts. Each year, the *Institutional Investor magazine* (*II* magazine hereafter) sends out a survey to research directors, money managers and buy side analysts in major asset management firms, collects their votes awarded to their favored sell side analysts and publishes the All-America Research Team (AART) ranking. The goal of AART (star analyst hereafter) ranking is not simply ranking stock pickers, but to "help the institutions decide what they will read, and who they will follow, for context and perspective"[20]. Studies find that star analysts are better than non-star analysts at forecasting earnings and picking stocks (Stickel (1992), (Leone, Wu (2007)), star analyst recognition is strongly associated with sell side analysts' compensation (Groysberg, Healy and Maber (2011)) and promotion (Leone, Wu (2007)).

However, just as existing literature has recognized the heterogeneity among institutional investors (Bushee (1998), Yan and Zhang (2007)), a heterogeneous group of institutional investors is responsible for

[20] Lowengard. M (2017, October) The Plot to Overthrow the All-America Research Team. *Institutional Investor magazine* Retrieved from https://www.institutionalinvestor.com/article/b1521gkf3q59ln/the-plot-to-overthrow-the-all-america-research-team

the selection of star analysts. Among all the institutional investors, hedge funds are a special group of investors that adopt trading strategies which may not be available to traditional asset managers. For example, the access to short selling and financial derivatives. Over the past few decades, the hedge fund industry is becoming more relevant as traditional money managers, such as pension funds, are allocating assets to hedge funds[21].

Due to the differences in investment strategy, hedge funds and traditional money managers could value different qualities of sell side analysts. Some anecdotes suggest this could be the story. For example, one portfolio manager in hedge fund Angelo, Gordon & Company[22] says "At a long-short hedge fund, you're looking to exploit small market inefficiencies or build a core position for maybe a 12-month time horizon. It's a different mentality from that of a big mutual fund, which may take a while to accumulate a position and then hold it longer." From the perspective of sell side analysts, Lehman Brother's Robert Willens, who was the No.1 best analyst voted by hedge funds in the area of accounting & tax policy in 2006[23], says "I speak almost exclusively to hedge funds at this point. Institutional investors are not interested in my research because it is best suited for making a particular trade rather than speaking to the long-term health of a company."

This paper aims to examine heterogeneity among sell side analysts by using a novel dataset. The *II* magazine star analyst ranking described above is well examined in prior analyst literature to proxy for skill and reputation. However, another star analyst ranking published by the sister magazine of *II* magazine, *Institutional Investor's Alpha* magazine (*Alpha* magazine hereafter), has received little attention in the

[21] "A growing number of institutional investors are building up their hedge fund portfolios to more than $1 billion. Over the past year 36 investors have joined Preqin's Billion-Dollar Club ranking of investors putting more than $1 billion into hedge funds, …This group of investors now accounts for 24 percent of total hedge fund industry assets under management, according to the study. Preqin points out that public pension funds account for the biggest group, representing 28 percent of the capital in the Billion Dollar Club."—Institutional investor's alpha magazine (May, 2017)

[22] Quotes are from Institutional Investor's alpha (2006 November/December Issue)

[23] From the best analysts ranking published by Institutional Investor's Alpha magazine in 2006.

literature. Different from *II* magazine, who uses votes from all the institutional investors (including hedge funds) in the survey as we discussed above, the *Alpha* magazine recounts votes only from hedge funds and generates a hedge fund version of All-America research team (sell side analysts) each year. Thus, we investigate whether hedge funds value different analyst attributes and abilities more or less than other institutional investors.

We find that both star analyst rankings have low turnover rates. In the subsequent one and two years, about 74.5% and 63.5% analysts, including the 1st, 2nd and 3rd places, remain on the *II* magazine star analyst ranking respectively. For the *Alpha* magazine ranking, the retention ratios of top three teams are 70.8% and 59.5% in the subsequent one and two years, respectively. The two rankings also have overlap—about 60% of the star analyst population show up in both rankings. Having overlap is not surprising by construction because the *Alpha* magazine star analyst ranking is based on a subset of votes that are used to generate the *II* magazine star analyst ranking. The fact that we do not have the data of star analysts voted by non-hedge fund institutions biases against us finding differences between the two populations.

We find that hedge funds preferred analysts generate forecasts more frequently. However, we do not find significant differences in terms of forecast accuracy and forecast boldness among the two types of star analysts. In the recommendation space, hedge funds favored analysts are significantly more likely to issue sell recommendation and their recommendation revisions have greater stock market impacts.

This paper adds to the understanding about interactions between sell side analysts and various types of institutional investors. Prior studies on this topic either investigate mutual fund managers or institutional investors in aggregate. For example, Cheng, Liu and Qian (2006) find that on average buy side analyst research is more important in the decision making process of US equity fund managers than sell side analyst research. Mola and Guidolin (2009) show that sell side analysts are more likely to assign favorable ratings to stocks after analysts affiliated mutual funds invest in the stock. Busse, Green and Jegadeesh (2012) use institutional investors' trading data and show that buy side trades follow sell side analyst research, but not the other way round. Brown, Wei and Wermers (2013) document that mutual funds trade together into stocks with consensus sell side analyst upgrades and out of stocks with consensus downgrades. Green, Jame, Markov and Subasi (2014) and Kirk and Markov (2016) show broker-hosted conference calls and firm-held analyst/investor days, respectively, are an important disclosure medium. However, these studies do not acknowledge the heterogeneity among institutional investors, which we think is important for a better understanding of sell side analysts' role in the capital market. One possible reason for such a gap in the literature is that we cannot directly observe the qualities valued by different investors (e.g., hedge funds vs. non-hedge funds). The data we use in this paper shows investors' revealed preferences — the best analysts in each industry from their perspective. Comparing the differences in investors' revealed preferences allows us to detect qualities valued by different investors.

This paper also contributes to the literature on cross sectional heterogeneity among sell side analysts. The popularity of star analyst designation motivates academic research on the quality of star analysts. Two frequently examined star analyst rankings include Institutional Investor's All-America research team (Merkley, Michaely, Pacelli (2017)) and Wall Street Journal's "star stock picker" (Groysberg, Healy and Maber (2011)). As we discussed earlier, the former surveys large buy side institutional investors and aggregates their votes to rank the top analysts in each industry while the latter ranks top analysts purely based on the performance of analysts' stock recommendations[24]. The results on star/non-star analysts' quality are mixed. For example, Emery and Li (2009) find that WSJ star analysts give worse stock recommendations after they become stars. Fang, Yasuda (2014) show that star analysts' recommendations are more profitable than non-star analysts' recommendations. We conjecture that the above two star analyst rankings might not fully capture sell side analysts' qualities valued by different clients, and by examining a novel dataset we are able to directly identify analysts preferred by different types of institutional investor —hedge funds vs. non-hedge funds institutions in this paper. We examine these two groups of investors for several reasons: 1) institutional investors in aggregate are very influential

[24] "Analysts' skill in picking stocks was measured using recommendation-performance scores calculated by FactSet Research Systems"—Wall Street Journal report, April 19, 2011

in the market (e.g., in 2010 they hold about 67% of equity[25] in the US stock market) and they are a major client of sell side analysts' research, 2) the difference between hedge funds and non-hedge funds institutional investors is stronger than the differences among long-only asset managers, 3) the hedge fund industry is growing and becoming more relevant in recent years.

We begin our study by examining the characteristics of star analysts ranking by *II* magazine and *Alpha* magazine. We show that *II* magazine star analyst ranking is highly persistent over time. Between 2004 and 2015, about 72% (57.3%) first team analysts remain the first team in the subsequent one (two) year(s). During the same time period, regardless of rank, about 74.5% and 63.5% of the II star analysts stay in the top three positions in the subsequent one and two years. In contrast, star analyst ranking voted by hedge funds are less persistent over time. The top three analysts (regardless of ranking) have a retention ratio of 70.8% and 59.5% in the subsequent one and two years, while the first team analysts have a retention ratio of 59.9% and 49%. We examine the differences in *II* magazine ranking and *Alpha* magazine ranking by decomposing star analysts into three mutually exclusive groups. Each year there are on average 205 star analysts (including the top three in each industry) in total, 126 (61.9%) of them show up in both rankings (common star analysts hereafter), 40 (19.4%) of them show up only in the A*lpha* magazine ranking (HF star analysts hereafter) and 38 (19.3%) of them show up only in the *II* magazine ranking (II star analysts hereafter). Since star analysts are voted within each industry defined by *II* magazine, we show that among all the industries (about 58 industries each year) covered by the ranking, 21% of them (on average 12 industries) have completely different top-three best analysts.

We next show that star analysts cover more stocks and industries than non-star analysts on average. Among star analysts, the difference in the breadth of coverage is not economically different, although an

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[25] Marshall E. Blume and Donald B. Keim, Working Paper, Institutional Investors and Stock Market Liquidity: Trends and Relationships, The Wharton School, University of Pennsylvania (Aug. 21, 2012), available at http://finance.wharton.upenn.edu/~keim/research/ChangingInstitutionPreferences_21Aug2012.pdf, at p.4.
See, also, The Conference Board, 2010 Institutional Investment Report: Trends in Asset Allocation and Portfolio Composition (November. 2010) ("Conference Board Report")

average HF star analysts cover more stocks (15.86) and industries (3.55) than an average II star analysts do (14.64 stocks and 3.30 industries on average). We find that star analysts revise earnings forecasts more frequently, with an average 7.68 revisions per firm per year by an average HF star analyst and an average 7.43 revisions per firm per year by an average II star analyst. In the univariate, we do not find significant difference in terms of earnings forecast accuracy and boldness among all the sell side analysts, which is consistent with findings in Emery and Li (2009).

There are some differences among stocks covered by each analyst group. On average, stocks covered by II star analysts are less volatile, have higher market capitalization, lower trading volume and lower sales growth rate than stocks covered by HF star analysts.

Our regression results show that although star analysts have better forecast accuracy and lower forecast boldness than non-star analysts, there is not a statistically significant difference in terms of forecast accuracy or boldness among the three star analysts groups. Controlling for analysts' forecast accuracy, boldness, analysts' general experience, and affiliated brokerage, the multinomial regression results show that forecast frequency is associated with a higher probability of being a HF star analyst than an II star analyst. Such findings are consistent with hedge fund managers valuing more frequent research due to their short term investment horizon.

We next show that on average HF star analysts issue less optimistic stock recommendations than II star analysts. The ordered logit model show that after controlling for firm and analyst characteristics, a HF star analyst has a 8% lower probability[26] (p-value=0.045) of issuing strong buy recommendation versus non-strong buy recommendations than a non-star analyst on average. In contrast, an II star analyst has a 3.6% higher probability (p-value=0.46) of issuing strong buy recommendation versus non-strong buy

[26] Probability is converted using the formula probability=odds/ (1+odds), where odds = exponential (log odds).

recommendation than a non-star analyst on average. Further test shows that HF star analyst and II star analyst are statistically different in expressing pessimism in stock recommendations.

We also find that the market responds differently to recommendation revisions made by different star analysts. We show that upward (downward) revisions made by HF star analysts are associated with significantly positive (negative) cumulative stock returns in the subsequent six months while recommendation revisions made by II star analysts are not. The difference between market responses to HF star analysts' revision and II star analysts' revisions are statistically significant in the subsequent six months. Such findings suggest that HF star analysts provide clients unique information that is not available through II star analysts.

Following Jegadeesh and Kim (2009), we investigate potential herding behavior in analysts' recommendations by examining the stock market response to analysts' recommendation deviations from the consensus. The model in Jegadeesh and Kim (2009) shows that the deviation of the new recommendation from the consensus would not impact market if the recommendation revision itself has the complete new information. Thus, positive responses from the market to new recommendations that positively deviated from the consensus suggest that analysts have incentive to herd. And a negative market response to new recommendations that positively deviation from the consensus suggests anti-herding incentive. The regression results show that the market does not differentiate between deviations made by HF star analysts, II star analysts and non-star analysts.

In conclusion, this paper investigates cross sectional differences among sell side analysts that are associated with their clienteles. We find that hedge fund favored analysts provide more frequent earnings forecasts and issue less optimistic stock recommendation. Their recommendation revisions also contain unique information that is not available in recommendation revisions made by analysts favored by other institutional investors.

The rest of the paper are organized as the following: section II develops testable hypotheses, section III discuss the data and methodology, where the key variables are constructed. Section IV analyzes the empirical results and section V concludes.

2. Hypothesis Development

In this section, we discuss the hypotheses examined in this paper. First of all, prior research suggests that institutional investors differ in their investment horizon (Bushee (1998), Yan and Zhang (2007)). Hedge funds use investment strategies, such as event-driven trades, to take advantage of short term price fluctuation. Anecdotes from industry suggest that hedge funds are more interested in short term price movements than traditional money managers such as mutual funds or pension funds. For example, an article on the October issue of Institutional Investor magazine in 2005 quotes portfolio strategist Francois Trahan of Bear, Stearns & Co "With hedge funds all that matters is the next quarter; with mutual funds it was 18 months." In the same year, Heather Bellini of UBS, the 2005 hedge fund-voted best sell side analyst in software category, is praised by hedge fund Agnos Group for research frequency and incremental information that helps pick stocks. Based on these evidence, we conjecture our first hypothesis that HF star analysts provide more frequent earnings forecast and stock recommendations compared to II star analysts.

Because of their different investment approaches it would not be surprising for hedge funds to short sell stocks, pension or mutual funds rarely do so. Hence, we conjecture that hedge funds, rather than traditional long-only money managers, are more likely to value unfavorable opinions from sell side analysts because they can short poor performing stocks. Hedge funds are also more tolerant with investment volatility and have a greater appetite for small and midcap stocks than other institutional investors. Therefore, our second hypothesis includes that 1) HF star analysts provide less optimistic stock recommendations than II star analysts; 2) stocks covered by HF star analysts differ from those covered by II star analysts in terms of volatility, size and returns.

Our third hypothesis is related to potential herding behavior among different analyst segments. Specifically, we are interested in two questions: 1) whether hedge fund (or Institutional Investor) star analysts are more likely to be the leader who makes the first forecast; 2) whether hedge funds star analysts generate bolder earnings forecasts and stock recommendations compared with the consensus than institutional investor star analysts, or otherwise. Theoretical models have proposed several rationales for herding behavior: reputation and career concern (Scharfstein, Stein (1990), Zwiebel (1995)), information cascade (Banerjee (1992), Bikhchandani, Hirshleifer, Welch (1992)), self-assessed abilities (Trueman (1994)) and highly correlated private information signal (Graham (1999)). For star analysts, the incentive to provide unique value-added information to their clients attenuates the likelihood to herd. Hedge fund star analysts and institutional investor star analysts could differ in their information sets. In a 2007 interview with Institutional Investor's alpha magazine, Gregory Ransom, the global head of equity research for Bank of America Securities said "Hedge funds are continually looking for actionable ideas and proprietary data that will give them an edge over their competitors". Using proprietary data to get an edge is not new for sell side analysts. For example, Bank of America's Daniel Oppenheim, ranked No.2 in homebuilders & building products in 2007, developed a proprietary monthly survey of residential real estate agents and has helped fund managers identify trade ideas in the subprime mortgage and homebuilding areas. If these analysts update their earnings forecast and stock recommendation in a timely fashion which incorporates such private information signals, it's plausible that other analysts would rationally mimic their actions.

Our last hypothesis focuses on star analysts' ability to forecast earnings and pick stocks. Different from the Wall Street Journal star analyst ranking, which is generated based on the performance of analysts' recommendations, II star analysts and HF star analysts are valued by qualities such as access to management, industry expertise and accessibility/responsiveness. In contrast, stock recommendations and earnings forecasts are ranked the 10th and 11th in the list of qualities valued by buy side investors from a 2007 survey by Institutional Investor magazine. Some suggest that buy side clients use the information provided by analysts to make their own investment decision instead of following analysts' stock recommendation directly. For example, Stuart Linde, New York based director of Americas equity research at Barclays, says "Analysts are being asked to mine their networks of industry contacts for certain data points that hedge fund portfolio managers can piece together for their own investment theses." Others suggest that analysts' stock recommendations are valued. For example, Steven Tighe, Merrill Lynch's head of Americas equity research, in New York says "Most stocks do not trade like flat liners, so we want analysts to figure out whether they are outperforms or underperforms. That's where alpha-generation is."

It's an empirical question whether there are skill differences inside the star analyst population. Following prior literature, we examine earnings forecast error to evaluate analysts' forecast ability, and buy and hold stock returns after recommendation announcement to infer analysts' stock picking ability.

3. Data and Methodology

Our data come from the following sources: analysts' quarterly earnings forecast and stock recommendation are from I/B/E/S; stock information and firms' financial information are from CRSP and Compustat, respectively; the Institutional investor star analyst ranking is from the annual Institutional Investor All-American research team published by *Institutional Investor* magazine; and the hedge funds star analyst ranking is from the annual hedge funds voted All-American research team published by *Alpha* magazine, a sister publication of *Institutional investor* magazine.

The annual All-American research team published by *Institutional Investor* magazine has been frequently examined by prior analyst research. Each year, the magazine sends out survey to large buy side institutional investors (e.g., portfolio managers and buy side researchers) and rank sell side research teams by counting votes from those institutional investors, including hedge funds. Its sister magazine, *Institutional Investor's Alpha* (*Alpha* magazine), extracts only the ballots cast by hedge funds and re-tabulates the winners of the election. Therefore, the best analysts ranking published by *Alpha* magazine is generated from a subset of votes that produce the *II* All-star analysts. We collect the hedge funds star analysts from the alpha magazine from 2004 to 2008 and from 2012 to 2016[27].

We take the top three research teams (i.e., 1st, 2nd and 3rd places) within each industry in each ranking as star analysts and examine four mutually exclusive groups of analysts in this paper: 1) star analysts who only show up in the best analyst ranking voted by hedge funds (HF star analysts); 2) star analysts who only show up in the best analyst ranking voted by institutional investors (II star analysts); 3)

[27] Due to magazines merge in 2009, the ranking data is not published from 2009 to 2011.

star analysts who show up in both best analyst rankings (common star analysts) and 4) non-star analysts who are the rest analysts in I/B/E/S database.

3.1 Analysts earnings forecasts

We follow Hong, Kubik and Solomon (2000) and Ke and Yu (2006) to create forecast accuracy and boldness measures. Our measures are constructed with quarterly earnings forecasts and actual earnings realizations. For a given firm in fiscal quarter t, we keep analysts' forecasts made between the announcement of actual earnings of fiscal quarter t and the announcement of actual earnings of fiscal quarter t-2.

To measure forecast accuracy, we first create an analyst-firm level measure using the absolute difference between an analyst' forecast, $F_{i,j,t}$ and the actual EPS, $A_{j,t}$ of firm j as shown in equation (1). We use the most recent quarterly EPS forecast issued by analyst i on stock j for fiscal quarter t before the announcement of actual earnings:

$$forecast\ error_{i,j,t} = \left|F_{i,j,t} - A_{j,t}\right| \tag{1}$$

Since we are interested in cross sectional heterogeneity across the star analyst population, we want to compare forecast ability at the analyst level. We next create a measure of analyst level forecast error, which attenuates the noise from different stocks covered by the analyst. The method is the same as in Hong, Kubik and Solomon (2000). First, we sort all analysts who cover the same stock j in quarter t based on the absolute value of their forecast error; then we assign a ranking based on the sorting results in the first step so that the analyst that made the most accurate forecast receives 1 as the rank value and the least accurate analyst receives N, which is the number of analysts covering stock j, as the rank value[28]. The rank captures an analyst's relative accuracy among all the analysts covering the same stock. By construction, thinly covered

[28] For the situation where multiple analysts are equally accurate, we follow Hong, Kubik and Solomon (2000) and assign all those analysts the midpoint value of the ranks.

stocks help analysts gain a lower rank that suggests better forecast accuracy. To mitigate such bias, we follow Hong et al. (2000) and compute a score for each analyst using equation (2):

$$Score_{i,j,t} = 100 - \left[\frac{rank_{i,j,t} - 1}{number\ of\ analysts_{j,t} - 1}\right] * 100 \tag{2}$$

where $rank_{i,j,t}$ is the rank value assigned to analyst i in the previous step and $number\ of\ analysts_{j,t}$ is the number of analysts covering stock j in the same quarter t[29]. The higher the value of score, the more accurate the forecast $F_{i,j,t}$ is. For example, the most accurate analyst receives 1 for $rank_{i,j,t}$ and his/her score is 100. For the least accurate analyst, the values of $rank_{i,j,t}$ and $number\ of\ analysts_{j,t}$ are the same and his/her score is 0. Finally, we take average of all the scores analyst i receives for all the stocks s/he covers in quarter t as the quarterly analyst level forecast error measure. To further reduce the noise due to changes in the set of stocks covered by an analyst over time, we take the average of the four quarterly scores before the release of all-star analysts ranking as the annual measure of accuracy. We acknowledge that the score measure will be in the extremes for analysts who forecast thinly covered stocks, to help mitigate this issue we require each stock to be covered by at least four analysts each quarter in the sample.

The second key measure based on analysts' earnings forecast is forecast boldness, which is often used in prior studies to infer herding. Similar as before, we first create analyst-firm level forecast deviation as in equation (3):

$$deviation\ from\ consensus_{i,j,t} = \left|F_{i,j,t} - \overline{F_{-\iota,\jmath,t}}\right| \tag{3}$$

$F_{i,j,t}$ is the first earning forecast made by analyst i to firm j for fiscal quarter t. $\overline{F_{-\iota,\jmath,t}} = {}^{1}\!/_{n} \sum_{m\epsilon-i} F_{m,j,t}$, where –i is the set of all analysts other than analyst i who forecast earnings of stock j in the same fiscal quarter, and n is the number of analysts in the set –i. $\overline{F_{-\iota,\jmath,t}}$ is the consensus forecast for stock j in fiscal quarter t, the average of the first forecasts (for the same fiscal quarter t) made by all other analysts excluding

[29] Stocks in the sample are required to be covered by at least four analysts.

analyst i. Based on the same logic, we create analyst-level boldness scores as we did for the accuracy measure above. We do the following steps: 1) sort all the analysts who cover stock j for fiscal quarter t based on their earnings deviation from the consensus; 2) assign each analyst a rank value based on the sorting results in step one, for example the analyst whose forecast deviates from the consensus the most receive a value of one; 3) create a score measure that captures each analyst's relative boldness and adjust for the number of analysts covering the same stock and 4) for each analyst i, take the average of boldness scores across all the stocks s/he covers for fiscal quarter t as the analyst level boldness measure.

3.2 Analyst stock recommendation

In this section, we discuss variables based on analysts' stock recommendations. We examine three questions related to stock recommendations: 1) do analysts differ in terms of the recommendations they give? 2) Does stock market react to recommendations issued by different analysts differently? And 3) Do certain analysts provide information by deviating from others' recommendations?

The third question is related to herding behavior among analysts. As prior studies point out, using analysts' earnings forecast to infer herding behavior could be problematic because analysts could receive the same information about earnings and it's hard to tell whether analysts are imitating others when they revise forecasts towards the consensus (Zitzewitz (2001), Jegadeesh and Kim (2009)). Welch (2000) argues that "Tests of informational cascades (Bikhchandani et al. (1992)) should focus on discrete rather than on continuous action choice scenarios" because discrete decisions give little room to use private information and to experiment with small changes. Jegadeesh and Kim (2009) point out that stock recommendations have an advantage in that market incorporates information in the consensus recommendation so that when analysts update their recommendation, they are not incorporating stale information in the consensus. In contrast, analysts rationally incorporate information in the consensus earnings forecast even if it's stale when they revise earnings forecasts. Therefore we examine analysts' stock recommendation by following Jegadeesh and Kim (2009) and restrict the sample by these rules: 1) for each stock in the sample, there should be at least one analyst who issues a recommendation and revises the recommendation within 180 calendar days; 2) there are at least two analysts other than the revising analyst who have active recommendations[30] for the same stock on the day before the revision; 3) the stock return is available on CRSP for the stock on the revision date; 4) the stock price is greater than $1 on the day before the recommendation revision date. If an analyst makes multiple recommendations during the past 180 days, we keep his/her latest two recommendations in the sample to measure the revision. We construct the stock recommendation consensus as the following: for each stock recommendation revision made by analyst i on date t, the consensus recommendation ($consensus_{j,t-1}$) is the average of the latest recommendations by analysts other than analyst i as of the day before t. The signed deviation of recommendation by analyst i for stock j in date t is defined as in equation (4).

$$Dev_{i,j,t} = rec_{i,j,t} - consensus_{j,t-1} \tag{4}$$

We construct a measure *leader-follower ratio (LFR)* to identify leader analysts by following Cooper, Day, and Lewis (2001) and Jegadeesh and Kim (2009). The intuition is that recommendations that are not immediately after the latest recommendations but are immediately followed by other recommendations are leaders. To be specific, for each stock recommendation revision in our sample, we locate the two recommendations issued by different analysts just before the revision date[31] and compute the number of days between the revision date and the announcement dates of the two recommendations, days_before1 and days_before2. We repeat the same steps, select the two recommendations issued by different analysts just after the revision date and compute days_after1 and days_after2. The leader-follower ratio (LFR) is defined as in equation (5) for analyst j who made k stock recommendations during a year. A high value of LFR suggests higher likelihood of being leader. The variable Leader analyst is one if the analyst is in the top 10 percentile in the population based on his/her LFR.

$$LFR_j = \frac{\sum_{k=1}^{K}(days\_before1_{j,k} + days\_before2_{j,k})}{\sum_{k=1}^{K}(days\_after1_{j,k} + days\_after2_{j,k})} \tag{5}$$

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[30] Stock recommendation are considered as active if it's within 180 days from the announcement date. We do this to remove stale recommendations.

[31] Recommendations on the same day are not included to compute leader-follower ratio.

3.3 Control variables

Prior studies have shown that firms' information environment and analysts' characteristics impact analysts' earnings forecast (Hartford, Jiang, Wang and Xie (2017)) and stock recommendations (Jegadeesh, Kim, Krische, and Lee (2004)). In the multivariate regressions, we include the following firm level and analyst level characteristics: cumulative subsequent twelve month stock return, institutional ownership, stock's idiosyncratic volatility, trading volume, sales growth, firm size (i.e., log of market capitalization), Amihud illiquidity, dividend yield, capital expenditure, analyst coverage (i.e., number of analysts covering the stock), analyst experience (i.e., the number of years the analyst exist in I/B/E/S) and first analyst dummy, which is 1 if the analyst makes the first earnings forecast for a stock in a given fiscal quarter. Table 2.9 has a detailed description of each control variable.

4. Empirical Tests and Analysis

We start the analysis by first describing the all-star analyst ranking data. Since we have eight years of matched ranking data, including 1st, 2nd and 3rd places of both institutional investor and hedge funds voted star analysts, we report summary statistics (e.g., retention ratios) on how persistent each analyst ranking is during the subsequent two years after the election year. Table 2.1 shows that both *II* magazine and *Alpha* magazine rankings are persistent over time. In 2004 there are 61 top one analysts in the *II* magazine ranking. In the next year 2005, 50 of the 61 (81.97%) top analysts remain top analysts in the *II* magazine ranking. In year 2006, 33 of the 61 (54.10%) top analysts in 2004 remain the top one analysts in the *II* magazine ranking. In panel B, we group the top three analysts in each industry. For example, in year 2005, there are 178 star analysts in the *II* magazine ranking and 179 star analysts in *Alpha* magazine ranking. In the next year 2006, 133 of the 178 star analysts remain in the top three in *II* magazine ranking and 124 of the 179 star analysts remain in the top three in *Alpha* magazine ranking. Between 2004 and 2015, about 72% (57.3%) top one *II*-star analyst remain the top one in the subsequent one (two) year(s). During the same time period, regardless of rank, about 74.5% and 63.5% of the *II* star analysts stay in the top three in the subsequent one and two years respectively. In comparison, star analyst ranking voted by hedge funds are less persistent over time. The top three analysts (regardless of ranking) have a retention ratio of 70.8% and 59.5% in the subsequent one and two years, while the top one analysts have a retention ratio of 59.9% and 49%.

Table 2.2 reports more summary statistics in *II* magazine ranking and *Alpha* magazine ranking. We segment all-star analysts into one of three mutually exclusive groups (i.e., HF star analysts, II star analysts and common star analysts) and then count the number of star analysts in each group each year and report the numbers in panel A. For example, in 2004 there are 224 (=43+47+134) star analysts in total, 43 of them (20%) only show up in *Alpha* magazine ranking, 47 of them (20%) only show up in *II* magazine ranking and 134 of them (61%) show up in both rankings. Across the sample period, each year there are on average 205 star analysts (including the top three in each industry) in total, 126 (61.9%) of them show up in both rankings (common star analysts), 40 (19.4%) of them only show up in *Alpha* magazine ranking (HF star analysts) and 38 (19.3%) of them only show up in *II* magazine ranking (II star analysts). Since the star analyst ranking is voted on within individual industry as defined by *II* magazine, we report the number of industries with common star analysts in panel B. For example, in year 2004, there are 61 industries in both *II* magazine and *Alpha* magazine rankings. Among the 61 industries, 12 of them (19.6%) have completely different top three analysts, 20 of them (32.8%) have one common star analyst, 19 of them (31.1%) have two common star analysts and 10 of them (16.4%) have the same top three analysts regardless of rank. Over the sample period, there are about 58 industries each year, 21% of them (on average 12 industries) have completely different top three analysts.

We next examine analyst characteristics. Using analysts' quarterly earnings forecast data, we report summary statistics for each analyst group in table 2.3. In year t, we keep analysts' earnings forecasts made for fiscal quarter between March 31st in year t-1 and April 1st in year t. We do this to leave institutional investors time to evaluate analysts' forecasts because the star analyst ranking is released in October[32]. Each year we first compute the variable (e.g., number of stocks/industries covered) for each analyst, and then take the average across analysts within each analyst group (e.g., HF star analysts, II star analysts). Table 2.3 reports the time series average of each statistic over years in the sample period. For example, there are on average 130 common star analysts, 40 II star analysts, 39 HF star analysts and 3485 non-star analysts in each year. Analysts' experience is the number of years between the forecast year and the first year the analyst show up in I/B/E/S database. We show that star analysts are more experienced in general. For each analyst group, we count the number of stocks and industries covered by an average analyst. For example, an average HF star analyst covers 15.86 stocks (3.55 industries) per year and an average II star analyst covers 14.64 stocks (3.30 industries) per year, much higher than the average 9.15 stocks (2.80 industries) covered by an average non-star analyst. We further show that besides the high breadth of coverage, star analysts also revise forecasts more frequently at the firm level. For example, an average HF star analyst makes 7.68 forecasts for a covered firm each year and an average II star analyst makes 7.43 forecasts for a covered firm each year.

Analysts who make the first forecast for a given firm is more likely to be the leader, however we acknowledge that this is a coarse herding measure as discussed in prior study (Hong, Kubik and Solomon (2000)) and include this statistic to better understand the sample. We report the percentage of first forecasts over total number of covered stocks for an average analyst in each group. The statistic suggests that star analysts on average make more first earnings forecast measured by the absolute value. Specifically, an average II star analyst makes the first forecast for 1.03 out of 14.64 (7.07%) stocks in a year while an average HF star analyst makes the first forecast for 1.14 out of 15.86 (7.20%) stocks in a year. An average

[32] The results are qualitatively similar if we keep the forecasts made in the 12 months prior each October in the sample.

common star analyst makes the first forecast for 1.27 out of 16.53 (7.69%) stocks in a year. In contrast, an average non star analyst makes the first forecast for 0.72 out of 9.15 stock.

We next report univariate statistics on analysts' forecast accuracy and boldness. As we discussed earlier in section 3, the accuracy score ranges between 0 (least accurate) and 100 (most accurate) and measures the relative accuracy rank of an analyst among all the analysts covering the same stock. The analyst level accuracy score suggests that star analysts have better accuracy than non-star analysts, which is consistent with Stickel (1992) and Leone and Wu (2007). Among star analysts, on average II star analysts have the highest accuracy score 51.25 and the lowest standard deviations. An average common star analyst and HF star analyst have accuracy score of 50.95 and 50.85 respectively. These accuracy score suggests that on average if we rank analysts based on their forecast accuracy, II star analyst is followed by common star analysts, HF star analysts and non-star analysts at last. The boldness score is similar to accuracy score, which ranges between 0 (closest to the consensus) and 100 (deviates the most from the consensus). II star analysts and HF star analysts have the same average boldness score, 50.68. In comparison, common star analysts and non-star analysts have a lower boldness score, although the economic magnitudes do not differ much.

We complete our summary statistics by examining the characteristics of firms covered by each group of analysts. Table 2.4 shows the time series average of cross sectional mean of each firm level characteristics in the earnings forecast sample. We construct the sample in the same way as we did in table 2.3. In year t, we keep the unique stocks covered by all analysts in one of the four mutually exclusive analyst groups and match these stocks with firm level characteristics computed at the end of March in year t. We follow Jegadeesh and Kim (2009) to construct each variable and winsorize firm characteristics at the 1st and 99th percentiles each year. We compute each variable for each stock, calculate the cross sectional distribution within each analyst group (as well as the difference between II star analysts and HF star analysts) and report the time series average of the mean (and t statistic) in table 2.4. The first four columns in table 2.4 shows the average characteristics of covered firms by each analyst group, and the last column shows the difference between characteristics of stocks covered by II star analysts and HF star analysts. We find that firms covered by HF star analysts have lower stock returns in the subsequent 12 months, higher idiosyncratic volatility, lower market capitalization and higher sales growth rates than those covered by II star analysts. These findings are consistent with the inference that hedge funds have a larger appetite for riskier stocks that are smaller and have higher volatility than traditional long-only asset managers, and thus have demand for information of these stocks from sell side analysts.

Following the univariate statistics, we next run multivariate regressions to test our hypotheses. Our first regression uses analyst-firm level earning forecast at each quarter. The dependent variable accuracy score (or boldness score) is at the individual earnings forecast level, where a high score suggests that this forecast is of relative low error compared to forecasts made by other analysts for the given firm in the given fiscal quarter. For example, $Accuracy\ score_{i,j,t}$ captures the relative accuracy of analyst i among all the analysts who cover firm j for fiscal quarter t. The regression is specified as in equation (6) below where we control firm and analyst level characteristics.

$$\begin{aligned} Accuracy\ score_{i,j,t} &= \alpha + \beta_1 HF\ star\ analyst + \beta_2 II\ star\ analyst \\ &+ \beta_3 Common\ star\ analyst + \beta_4 No.analyst\ following \\ &+ \beta_5 First\ analyst\ dummy + \beta_6 Analyst\ experience \\ &+ \beta_7 No.analyst\ following + \beta_8 Top\ brokerage\ dummy \\ &+ firm\ and\ analyst\ characteristic\ controls \\ &+ quarter\ fixed\ effect \end{aligned} \tag{6}$$

We include an HF star analyst dummy, which is equal to one when analyst i only shows up in the *Alpha* magazine ranking in year t. *II star analyst dummy* is equal to 1 when analyst i only shows up in the *II* magazine ranking in year t. *Common star dummy* is equal to 1 when analyst i shows up in both *II* magazine and *Alpha* magazine ranking in year t. *No. analyst following* is the number of analysts covering stock j for fiscal quarter t. *First analyst dummy* is equal to 1 when analyst i makes the first forecast for stock j in fiscal quarter t. *Analyst experience* is the number of years analyst i has been in the I/B/E/S database. *No. firms* *covered* is the number of firms covered by analyst i in fiscal quarter t. *Top brokerage dummy* is equal to 1 if analyst i is affiliated with a brokerage firm that has more than 20 analysts in year t. We include firm level characteristics such as size, idiosyncratic volatility, illiquidity, earnings-to-price ratio, dividend yield, and external financing.

Panel A in Table 2.5 shows the regression results. We report both OLS and Tobit model specification as the dependent variable Accuracy score ranges from 0 and 100. We control for firm characteristics such as size, earnings-to-price ratio, idiosyncratic volatility, illiquidity, dividend yield and external financing. We find that star analysts are significantly associated with better earnings forecast accuracy compared with non-star analysts, which is the base level in the regression. For example, the coefficients from the Tobit regression model suggest that an average II star analyst has an accuracy score that is 1.536 (t-statistic=3.45) higher than that of an average non-star analyst, meaning that if we rank all the analysts by their forecast accuracy for the same stock-fiscal quarter, on average II star analyst is ranked higher than non-star analyst. Similar interpretations apply to HF star analyst and common star analyst. Since we are interested in whether HF star analyst and II star analyst differ in their forecast accuracy, we test the hypothesis that the coefficient of HF star analyst equals the coefficient on II star analyst in the regression. We report the p-value of the test statistic in the bottom of panel A. The hypothesis cannot be reject as the p-values are above 10 percent in all three regression models. Therefore we do not find statistically significant evidence that HF star analysts and II star analysts differ in forecast accuracy. The results also show that the first forecast is associated with lower accuracy and forecasts from top brokerage are associated with higher accuracy.

We next replace the dependent variable with analyst-firm level boldness score in equation (6). The coefficient 0.794 on HF star analyst dummy (t-statistic=2.01) and coefficient 0.819 on II star analyst dummy (t-statistic=2.05) are significantly different from zero, suggesting that HF star analyst and II star analyst make bolder forecast than non-star analysts. However, the hypothesis that HF star analyst and II star analyst do not differ in their forecast boldness cannot be rejected since p-values of the test statistic in the three regressions (column 4, 5, and 6) are above 10 percent. The last two columns in panel A of table

2.5 examine the relation between analyst characteristics and the choice to make the first forecast for a given stock. The dependent variable is first forecast dummy, which equals 1 when analyst i makes the first forecast for stock j in fiscal quarter t. The coefficients on II star analyst, -0.013 (in OLS regression) and -0.183 (in Logit regression) are both statistically significant, consistent with II star analysts are less likely to issue the first forecast. The bottom p-value (0.1219 for OLS regression and 0.817 for Logit regression) in panel A are all above 10 percent, showing no evidence that II star analysts and HF star analysts are different in terms of being the forecast leader.

In panel B of table 2.5, we examine factors that are associated with being voted a star analysts. We use multinomial logistic regression where the dependent variable has four values, each representing an analyst group. The base group is II star analysts. Accuracy score and boldness score are at analyst-year level, which are computed by averaging analyst-firm-quarter accuracy (boldness) scores within each analyst over the four quarters before each October in year t. No. forecast is the total number of forecasts made by the analyst in year t. Top brokerage dummy is 1 when the analyst's affiliated brokerage has more than 20 analysts in year t. Percentage of first forecast is the number of first forecast scaled by the number of covered firms by the analyst over a four quarter period. We cluster the standard errors at analyst level to allow correlation within analyst over time. Panel B in table 2.5 reports the relative risk ratio minus one for each independent variable. The regression results suggest that the number of forecasts and affiliation with top brokerage firms are characteristics that differ between II star analysts and HF star analysts. Specifically, an increasing number of forecasts is associated with a higher likelihood (coefficients=0.002 and p-value less than 0.05) of becoming a HF star or common star analyst than II star analyst. Being affiliated with a top brokerage firm is associated with lower likelihood (coefficient= -1.058 and p-value=0.051) of becoming HF star analyst than II star analyst on average. The coefficients on accuracy score and boldness score are consistent with findings in the univariate test and firm level regressions, where we do not find statistically significant difference among star analysts in terms of forecast accuracy and boldness. Results in column (3) confirms our previous findings on the difference between star and non-star analysts, where non-star analysts on average are less accurate and bold, make fewer forecasts, have less experience and are less likely to be affiliated with top brokerage firm.

We next move to the stock recommendation sample. Following prior studies, we rescale the value of recommendations in I/B/E/S so that value 5 indicates strong buy and value 1 indicates strong sell. First of all, we test whether HF star analysts are less optimistic than II star analysts. As we discussed in the hypothesis development section, hedge funds are able to short sell and thus would appreciate negative opinions. Accordingly, we run ordered logit regression as well as OLS regression for robustness in table 2.6 where the dependent variable is recommendations made by individual analyst. Equation (7) shows the model specification,

$$\begin{aligned} recommendation_{i,j,t} &= \alpha + \beta_1 HF\ star\ analyst + \beta_2 II\ star\ analyst + \beta_3 Common\ star\ analyst \\ &+ \beta_4 Lead\ analyst\ dummy + \beta_4 Top\ broker\ dummy + firm\ characteristics \\ &+ quarter\ fixed\ effect \end{aligned} \quad (7)$$

where $recommendation_{i,j,t}$ is the recommendation made by analyst i for stock j at date t. *Leader analyst dummy* is equal to 1 if analyst i is among the top 10 percentile analysts in year t based on the leader-follower ratio (LFR) defined in section 3. Following Jegadeesh, Kim, Krische and Lee (2004) and Dechow, You (2013), we control for firm-level characteristics such as size, subsequent 12 months stock return, earnings-to-price ratio, stock idiosyncratic volatility, Amihud illiquidity, dividend yield and external financing.

The ordered logit model in table 2.6 shows that HF star analysts are associated with an 8% lower probability[33] of issuing a strong buy recommendation versus a non-strong buy recommendations than non-star analysts (p-value=0.045), after controlling for both analyst and firm level characteristics. II star analysts are associated with a 3.6% higher probability of issuing a strong buy recommendations versus a non-strong

[33] All probabilities are converted from log odds, which are the coefficients reported in table 2.6.

buy recommendations than non-star analysts (p-value=0.46) after controlling for both analyst and firm level characteristics. We notice that the signs of the coefficient of HF star analyst remain negative in all four model specifications and the signs of the coefficient of II star analyst remain positive in all four model specifications. As we did previously, we test the null hypothesis that HF star analysts and II star analysts do not differ in terms of recommendation optimism. The bottom panel in table 2.6 shows the p-value of the null hypothesis H0 under each regression specification. The null (coefficient of HF star equals coefficient of II star) is rejected in every specification. For example, in column (4) where we run OLS regression and cluster standard errors in firm and quarter level, HF star analyst dummy is negatively associated with recommendation value and II star analyst dummy is positively associated with recommendation value. The difference in the coefficients between HF star analyst and II star analyst is statistically significant at the 5% level. Such findings suggest that HF star analysts are less optimistic in making recommendations than II star analysts.

The recommendation itself does not show analysts' ability to pick stocks. We next examine the information contained in analysts' recommendations. Specifically, we look into the buy and hold abnormal returns in the subsequent six months after the announcement of each recommendation in our sample. The buy and hold abnormal return is constructed as in equation (8), where $ABR_i(t, t+H)$ is the abnormal buy and hold return between trading day t and trading day t + H for stock i as in Jegadeesh and Kim (2009).

$$ABR_i(t, t+H) = \prod_{\tau=t}^{t+H}(1 + R_{i,\tau}) - \prod_{\tau=t}^{t+H}(1 + R_{m,\tau}) \tag{8}$$

$R_{i,\tau}$ is the daily return of stock i and $R_{m,\tau}$ is the daily market benchmark return. We use CRSP value weighted stock index as the market portfolio[34] and examine different holding periods from the

[34] Results are robust if we use CRSP equal weighted index or S&P500 index.

announcement date (day 0) to the maximum holding period of six calendar month (126 trading days). Our model specification is described in equation (9).

$$ABR_i(t, t+H) = \alpha + \beta_1 \Delta rec + \beta_2 HF\ star\ analyst + \beta_3 II\ star\ analyst + \beta_4 Common\ star\ analyst + \beta_5 Leader\ analyst + \beta_6 HF\ star\ analyt\ \times \Delta rec + \beta_7 II\ star\ analyst\ \times \Delta rec + \beta_8 Common\ star\ analyst\ \times \Delta rec + \beta_9 Leader\ analyst\ \times \Delta rec + Year\ fixed\ effects + broker\ fixed\ effects \tag{9}$$

For each recommendation made by analyst i in the sample, Δrec is the signed change in the recommendation made by analyst i compared to his/her most recent one for the same stock. Table 2.7 reports the regression results. We show that Δrec is positively associated with abnormal buy and hold returns in the subsequent time periods. For example, one incremental increase in recommendation is associated with 1.7% market adjusted abnormal return (t-statistic=21.99) on the announcement date and 2.3% (t-statistic=15.62) market adjusted abnormal buy and hold return over the subsequent six months. Such findings are consistent with those in Womack (1996), which documents market drift over the subsequent six months after analysts revise recommendations. What we find interesting is the coefficient on the interaction term between HF star analyst and Δrec. Revisions made by HF star analysts are positively associated with future stock returns over six months. On average, one unit increase of recommendation made by HF star analysts are associated with 0.4% market adjusted abnormal return on the recommendation announcement date (t-statistic=1.78) and 1.2% market adjusted abnormal return (t-statistic=2.81) in the subsequent 126 trading days after the announcement date. In contrast, there is no statistically significant association between recommendation revisions made by II star analysts and subsequent abnormal buy and hold stock returns. The bottom panel in table 2.7 reports the p-value of the test for the null hypothesis that market responses to recommendations revised by HF star analysts and II star analysts do not differ. The hypothesis is rejected in every buy and hold period. These findings suggest that HF star analysts are providing information that is not available from II star analysts[35].

Our last test is related to analysts' herding behavior. We define herding as moving towards consensus that is not due to information. For stock i that receives a recommendation $new\_rec_{i,j,t}$ from analyst j on date t, we define $consensus\_rec_{i,t-1}$ as the average of all outstanding active recommendations by other analysts as of the day before the revision date. We follow Jegadeesh and Kim (2009) and require the 180 calendar days as active period for each recommendation. We then run the model specification in equation (10),

$$
\begin{aligned}
ABR_i(t, t+H) = \alpha + \beta_1 \Delta rec + \beta_1' \left(new\_rec_{i,j,t} - consensus\_rec_{i,t-1}\right) + \\
\beta_2 HF\ star\ analyst + \beta_2' HF\ star\ analyst \times \left(new\_rec_{i,j,t} - consensus\_rec_{i,t-1}\right) + \\
\beta_3 II\ star\ analyst + \beta_3' II\ star\ analyst \times \left(new\_rec_{i,j,t} - consensus\_rec_{i,t-1}\right) + \\
\beta_4 Common\ star\ analyst + \beta_4' Common\ star\ analyst \times \left(new\_rec_{i,j,t} - \right. \\
\left. consensus\_rec_{i,t-1}\right) + \beta_5 Leader\ analyst + \beta_5' Leader\ analyst \times \left(new\_rec_{i,j,t} - \right. \\
\left. consensus\_rec_{i,t-1}\right) + quarter\ fixed\ effects + Broker\ fixed\ effects
\end{aligned} \qquad 10)
$$

where $ABR_i(t, t+H)$ is the buy and hold abnormal return as we defined in equation (9). Deviation is the signed difference between $new\_rec_{i,j,t}$ and $consensus\_rec_{i,t-1}$ for stock i on date t when analyst j made a recommendation revision. Δrec is the signed stock recommendation made by analyst j for stock i on date t. According to the model in Jegadeesh and Kim (2009), if analysts herd toward consensus without information, stock returns will be positively related to the deviations from the consensus. In other words, positive coefficients on signed deviation is consistent with analysts in aggregate have incentive to herd. If analysts tend to exaggerate recommendations, meaning they intentionally deviate recommendations from

[35] For robustness check, we exclude iteration recommendations from the sample and the results are quantitatively similar.

the consensus, stock returns will be negatively related to the deviations from the consensus and we will observe a negative coefficient on the deviation is consistent with this situation. The assumption is that stock market incorporates information efficiently, and when analysts tend to herd without information, the market values information when certain analyst deviate from the consensus.

Table 2.8 reports the regression results. We find that signed deviation is positively associated with the market adjusted stock returns on announcement day 0 and in every buy and hold period after controlling for the recommendation revision. One unit positive deviation from the consensus is associated with 0.5% market adjusted return (t-statistic=6.56) in the subsequent three trading days following the announcement of the recommendation. The coefficient on deviation is increasing over time and the same one unit positive deviation is associated with 1% abnormal market adjusted return in the subsequent six months. Such evidence suggests that analysts have the tendency to herd, which is consistent with the finding in Jegadeesh and Kim (2009). We next examine whether the market reacts differently to deviations made by different star analysts. We interact each signed deviation with the identity of the analyst who makes the revision. We find the coefficient on the interaction term with HF star analysts are not statistically different from zero in the subsequent six months after the announcement of the recommendation. Similar finding apply to II star analysts and common star analysts. We last test the null hypothesis that market do not reacts differently to deviations made by HF star and II star analysts and we do not find statistically significant evidence to reject the null.

5. Conclusion

In this paper, we examine whether there are cross sectional differences among sell side star analysts. We use a novel dataset which allows us to identify sell side analysts that are considered the best by a unique group of buy side institutional investors—hedge funds. Due to the significant differences in investment strategies and styles between hedge funds and traditional long-only investors, we conjecture that analysts favored by hedge funds might differ in their research frequency and ability to pick stocks. The findings from our tests are generally consistent with what we learned from the interviews with practitioners in the industry. Hedge fund voted best analysts cover more stocks and make updates more frequently per firm. However, we do not find significant differences in terms of forecast accuracy and forecast boldness between hedge funds favored analysts and other star analysts. In the recommendation sample, we find that hedge fund star analysts are more likely to express pessimistic opinions than institutional investor star analysts, consistent with that fact that hedge funds value unfavorable opinions. Stock markets also respond more strongly to recommendation revisions made by hedge fund star analysts, in contrast, we do not have significant market response to revisions made by star analysts not favored by hedge funds. In conclusion, our findings suggest that there are cross sectional differences among sell side analysts that are associated with clients' needs.

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Appendix

Table 2.1 All-America Research Team Ranking Persistence

This table reports the number of analysts on the annual All-America research team ranking published by *Institutional Investor* magazine and *Institutional Investor's Alpha* magazine each year between 2004 and 2016. Analysts that cannot be found in I/B/E/S database are excluded from this table. Between 2009 and 2011 *Alpha* magazine did not publish the best analysts picked by hedge funds, therefore statistics are missing in those years. In 2012, we only have the top one analyst in each industry voted by hedge funds. In 2016, we only have the top one analyst in each industry voted by institutional investors. Panel A includes only the top one analyst in each industry and Panel B includes the top three analysts in each industry on each ranking and. # star Yr 0 shows the number of star analysts in year 0, # star Yr+1 shows the number of star analyst who were among the top three (or the top one) in year 0 and remain among the top three (or the top one) in year +1. Retention shows the retention ratio.

Panel A Top one analysts in each ranking

	II magazine ranking					Alpha magazine ranking				
Year	# star Yr 0	# star Yr+1	retention	# star Yr +2	retention	# star Yr 0	# star Yr +1	retention	# star Yr +2	retention
2004	61	50	81.97%	33	54.10%	61	38	62.30%	34	55.74%
2005	61	39	63.93%	34	55.74%	61	37	60.66%	31	50.82%
2006	60	41	68.33%	31	51.67%	60	38	63.33%	28	46.67%
2007	58	41	70.69%	34	58.62%	58	32	55.17%		
2008	56	39	69.64%	32	57.14%	56				
2009	56	40	71.43%	35	62.50%					
2010	56	40	71.43%	34	60.71%					
2011	57	41	71.93%	35	61.40%					
2012	56	44	78.57%	36	64.29%	55	39	70.91%	27	49.09%
2013	54	41	75.93%	31	57.41%	54	34	62.96%	29	53.70%
2014	52	39	75.00%	24	46.15%	53	26	49.06%	20	37.74%
2015	49	32	65.31%			49	27	55.10%		
2016	45					45				

Table 2.1 Continued

Panel B Top three analysts in each ranking										
	II magazine ranking					Alpha magazine ranking				
2004	181	139	76.80%	113	62.43%	177	130	73.45%	109	61.58%
2005	178	133	74.72%	103	57.87%	179	124	69.27%	94	52.51%
2006	174	124	71.26%	98	56.32%	168	109	64.88%	85	50.60%
2007	170	117	68.82%	103	60.59%	166	97	58.43%		
2008	165	121	73.33%	111	67.27%	165				
2009	163	130	79.75%	111	68.10%					
2010	164	124	75.61%	112	68.29%					
2011	167	127	76.05%	114	68.26%					
2012	162	119	73.46%	100	61.73%	55	48	87.27%	39	70.91%
2013	161	122	75.78%	103	63.98%	160	113	70.63%	97	60.63%
2014	158	117	74.05%			153	110	71.90%	93	60.78%
2015	148					149	105	70.47%		
2016	45					136				

Table 2.2 Description of All-America Research Team Ranking

Panel A reports the number of star analysts (including 1st, 2nd, and 3rd places on the ranking) who only show up in the star ranking voted by hedge funds (No. HF star analysts), the number of star analysts who only show up in the ranking by institutional investors (No. II star analysts) and the number of star analysts on both hedge fund and institutional investors ranking (No. common star analysts). Panel B reports the total number of industries covered by the ranking in each year and the number of industries that have no common star analysts, one common star analyst, two common star analysts and three common star analysts in each year.

Panel A number of analysts in each star category			
Year	No. HF star analysts (%)	No. II star analysts (%)	No. Common star analysts (%)
2004	43 (20%)	47 (20%)	134 (61%)
2005	42 (19%)	41 (19%)	137 (62%)
2006	32 (16%)	38 (18%)	136 (66%)
2007	38 (19%)	42 (19%)	128 (63%)
2008	42 (21%)	42 (20%)	123 (59%)
2013	43 (21%)	44 (21%)	117 (58%)
2014	31 (19%)	36 (19%)	122 (65%)
2015	36 (19%)	35 (19%)	113 (61%)

Panel B number of industries with different numbers of common star analysts								
	2004	2005	2006	2007	2008	2013	2014	2015
# common star analysts	# of industries							
0	12	14	12	14	10	12	12	11
1	20	24	25	15	25	26	17	21
2	19	12	15	22	15	12	16	9
3	10	12	9	8	7	7	11	11
Total No. Industries	61	62	61	59	57	57	56	52

Table 2.3 Descriptive Statistics by Analyst Groups

This table reports characteristics of an average analyst in each group in the earnings forecast sample. We take the top three research teams (i.e., 1st, 2nd and 3rd places) in each ranking as star analysts and examine four mutually exclusive groups of analysts in this paper: 1) star analysts who only show up in the best analyst ranking voted by hedge funds (*HF star analysts*); 2) star analysts who only show up in the best analyst ranking voted by institutional investors (*II star analysts*); 3) star analysts who show up in both best analyst rankings (*common star analysts*) and 4) *non-star analysts* who are the rest analysts in I/B/E/S database The sample requires at least four analysts covering the same stock each quarter. I compute each variable for each analyst each year, then take the average across all the analysts within each analyst group each year and report the time series average of the statistics over eight years. Column N reports the rounded average number of analysts in each analyst group each year in the sample. *Analysts' experience* is the number of years the analyst exists in I/B/E/S database. *Number of covered firms/industries* is the number of firms/industries covered by each analyst in the 12 months before each April in the year star analyst ranking is released. *Percentage of first forecasts over number of covered firms* is the number of times an analyst gives the first earnings forecast scaled by the number of firms covered in a year. *Number of forecasts revision per firm per year* is the number of total earnings forecasts an average analyst makes during a year over the number of firms covered in a year. *Accuracy score* and *boldness score* (value between 0 and 100) are constructed as in Hong, Kubik and Solomon (2000) and measure the rank of forecast accuracy and boldness among all the analysts that cover the same stock[36] in the same quarter. Higher value of accuracy (boldness) score indicates better accuracy (bolder forecast).

Summary statistics for analysts' earnings forecast in each category								
Analyst group	N	Mean	Min	Max	St. Dev	P25	P50	P75
	Analysts' experience (number of years)							
Common star analysts	130	16.94	2.13	27.50	7.42	10.75	17.50	24.00
II-star analysts	40	16.35	2.13	27.38	8.41	8.81	17.88	24.25
HF-star analysts	39	15.55	1.75	26.75	7.93	8.81	15.88	23.00
Non-star analysts	3485	10.56	0.00	29.00	8.70	3.00	7.69	18.13
	Number of covered stocks per year							
Common star analysts	130	16.53	3.13	51.13	7.25	11.75	15.94	19.63
II-star analysts	40	14.64	2.88	40.63	7.73	9.38	13.63	18.81
HF-star analysts	39	15.86	4.38	34.88	6.39	11.75	15.00	18.81
Non-star analysts	3485	9.15	1.00	62.38	6.82	3.13	8.38	13.50
	Number of industries covered per year							
Common star analysts	130	3.62	1.00	11.00	2.22	2.00	3.38	4.75
II-star analysts	40	3.30	1.00	9.88	2.18	1.50	2.69	4.56
HF-star analysts	39	3.55	1.00	9.38	2.09	2.00	3.25	4.81
Non-star analysts	3485	2.80	1.00	21.63	2.31	1.00	2.00	3.75
	Number of forecasts revision per firm per year							
Common star analysts	130	7.53	1.76	22.99	3.15	5.59	7.12	8.78
II-star analysts	40	7.43	2.17	16.78	3.05	5.48	7.12	8.96
HF-star analysts	39	7.68	2.65	18.61	3.25	5.76	7.16	8.91
Non-star analysts	3485	5.03	1	43.39	3.23	2.67	4.72	6.57

[36] I follow Hong, Kubik and Solomon (2000) and Ke and Yu (2006) to create performance and boldness score. A detailed description is in the methodology section.

Table 2.3 Continued

Analyst group	N	Mean	Min	Max	St. Dev	P25	P50	P75
	Percentage of first forecasts over number of covered firms (%)							
Common star analysts	130	7.69	0.00	50.83	9.14	1.44	4.95	10.54
II-star analysts	40	7.07	0.00	35.59	8.83	0.05	4.21	10.54
HF-star analysts	39	7.20	0.00	29.08	7.25	1.44	5.30	11.21
Non-star analysts	3485	7.84	0.00	100	12.91	0.00	2.83	10.85
	Accuracy score							
Common star analysts	130	50.95	25.61	73.71	7.12	47.11	51.18	55.35
II-star analysts	40	51.25	36.87	66.09	6.57	47.03	51.24	55.68
HF-star analysts	39	50.85	31.45	65.93	7.39	46.49	50.93	55.64
Non-star analysts	3485	48.67	0.00	100.00	14.17	42.86	49.81	55.56
	Boldness score							
Common star analysts	130	50.17	34.09	75.90	6.58	46.14	49.65	53.59
II-star analysts	40	50.68	34.23	71.85	7.63	45.72	50.34	54.51
HF-star analysts	39	50.68	37.99	65.95	6.36	46.26	50.04	54.48
Non-star analysts	3485	50.49	0.00	100.00	13.85	43.77	49.85	56.36

Table 2.4 Summary Statistics of Covered Firm Characteristics

This table reports the time series average of mean value of firm characteristics in the first calendar quarter of each year. The sample includes stocks covered by analysts (i.e., firms receive quarterly earnings forecast) in the previous 12 months before each April in years between 2004 and 2008 and 2013 and 2015. Column (1) includes stocks covered by common star analysts. Column (2) includes stocks covered by II star analysts. Column (3) includes stocks covered by HF star analysts. Column (4) includes stocks covered by non-star analysts. Star analysts include the 1st, 2nd and 3rd analysts on each ranking. The last column reports the difference between column (2) and (3) and t statistics are Newey-West adjusted with four lags. T statistics are in the parentheses. Variables are winsorized at 1st and 99th percentile. *Subsequent 12m cret* is the cumulative stock return in the subsequent 12 months. *Amihud illiquidity* is constructed as in Acharya, Pedersen (2005). *Idiosyncratic volatility* is measured by standard deviation of the residual in Fama French 3 factor regression with three month daily return data. *Size* is the natural log of market capitalization (in 000s). To compute *volume*, we first calculate the average daily trading volume over shares outstanding during the past six months, then sort the average daily turnover within the stock's listed exchange into 100 percentiles and then convert the percentile into 0 and 1 by dividing by 99. *Inst. ownership* is percentage of equity owned by institutional investors. We construct *sales growth rate* (%), *SUE* (standardized unexpected earnings), *dividend yield*, *BP ratio* (book-to-price) and *CAPEX/AT* (capital expenditure over total assets) as in Jegadeesh, Kim, Krische and Lee (2004).

Variable	Common star	II star	HF star	Non-star	diff
	(1)	(2)	(3)	(4)	(2)-(3)
Subsequent 12m cret	0.0398	0.0415	0.0396	0.0278	0.0018
					(0.26)
Amihud illiquidity	0.0016	0.0012	0.0011	0.0047	0.0000
					(0.16)
Idiosyncratic volatility	0.0158	0.0150	0.0156	0.0176	-0.0006**
					(-3.34)
Size	22.36	22.79	22.66	21.63	0.1218**
					(2.52)
Volume	0.6020	0.5741	0.5965	0.6025	-0.0225*
					(2.04)
Inst. ownership	0.7391	0.7252	0.7264	0.7139	-0.0013
					(-0.21)
Sales growth rate (%)	1.1192	1.1095	1.1282	1.1462	-0.0187**
					(-3.49)
SUE	0.1344	0.0943	0.1263	0.1120	-0.0321**
					(-2.41)
Dividend yield	0.0136	0.0150	0.0145	0.0112	0.0005
					(0.39)
BP ratio	0.4311	0.4237	0.4192	0.4340	0.0045
					(0.47)
CAPEX/AT	0.1172	0.1154	0.1219	0.1148	-0.0065
					(-1.01)

Table 2.5 Star Analyst Category, Earnings Forecast Accuracy and Forecast Boldness

Panel A reports the regression results using analyst-firm-quarter observations. The sample includes the forecasts made by analysts during the 12 months prior April each year before the release of star analyst ranking. *Accuracy score* (value between 0 and 100) measures an analyst' earnings forecast accuracy among all the analysts covering the stock. Higher value of performance score indicates better accuracy. *Boldness score* (value between 0 and 100) measures an analyst's forecast boldness among all the analysts covering the stock. The boldness score are based on the first forecast made by each analyst to a given stock for a given fiscal quarter. Analysts are ranked based on their forecasts deviations and assigned the boldness score based on the ranking. Higher boldness score indicates higher deviation from other analysts covering the same stock. *HF star analyst* is 1 when the analyst only appears on hedge funds voted best analyst ranking. *II star analyst* is 1 when the analyst only appears on institutional investors voted best analyst ranking, but not hedge funds voted best analyst rankings. *Common star analyst* is 1 when the analyst show up on both hedge funds and institutional investors' best analyst rankings. *Non-star analysts* are the rest analysts in the I/B/E/S database. *No. analysts following* is the number of analysts who cover the stock in a quarter. *First forecast dummy* is 1 if the analyst is the first analyst that forecasts the earning for the given stock in a given quarter. *Analyst experience* is the number of years the analyst has been in the IBES database by the quarter. *No. firms covered* is the number of firms covered by the analyst. *Top brokerage dummy* is 1 when the brokerage firm has more than 20 analysts in a year. Firm characteristics include: size, subsequent 12 month stock return, institutional ownership, Amihud illiquidity, idiosyncratic volatility, trading volume, sales growth, capital expenditure, and dividend yield. Firm characteristics are winsorized at 1st and 99th percentile. Panel B reports multinomial logistic regression results using analyst-year observations. The dependent variable *analyst group* has four values, which represent HF star analyst, II star analyst, common star analyst and non-star analysts. The base level is II star analysts and the reported coefficients are relative risk ratio minus one. *Percentage of first forecasts* is the number of first earnings forecast over the number of firms covered by an analyst in a year. *No. forecasts* is the number of earnings forecasts an analyst made over a year. *Accuracy score* is the average of four quarterly accuracy score over a year for an analyst. *Boldness score* is the average of the quarterly boldness scores over a year for an analyst.

Table 2.5 Continued

Panel A Analyst firm quarterly level regression								
	OLS Accuracy score	Tobit Accuracy score	OLS Accuracy score	OLS Boldness score	Tobit Boldness score	OLS Boldness score	OLS First forecast dummy	Logit First forecast dummy
HF star analyst	1.074***	1.145***	1.165***	0.794*	0.792**	0.205	-0.004	-0.158*
	(3.18)	(3.20)	(3.38)	(2.01)	(1.97)	(0.51)	(-0.97)	(-1.84)
II star analyst	1.408***	1.536***	1.100**	0.819**	0.838**	-0.149	-0.013***	-0.183**
	(3.36)	(3.45)	(2.46)	(2.05)	(2.03)	(-0.38)	(-2.97)	(-2.32)
Common star analyst	1.232***	1.349***	1.147***	0.031	0.041	-0.528*	-0.005	-0.186***
	(5.00)	(5.19)	(4.03)	(0.12)	(0.16)	(-1.94)	(-1.45)	(-3.49)
No. analysts following	-0.002	0.037***	-0.008**	0.006***	0.041***	0.011***	-0.004***	-0.063***
	(-1.30)	(15.91)	(-2.49)	(3.24)	(14.43)	(3.13)	(-20.04)	(-42.89)
First forecast dummy	-0.967***	-1.190***	-0.802***	2.041***	1.986***	2.152***		
	(-3.95)	(-4.39)	(-3.38)	(5.99)	(5.73)	(6.32)		
Analyst experience	-0.036***	-0.039***	-0.043***	-0.016**	-0.016**	0.003	0.003**	0.004***
	(-5.97)	(-5.87)	(-7.48)	(-2.06)	(-2.03)	(0.36)	(2.52)	(3.32)
No. firms covered	0.042***	0.046***	0.033**	-0.012	-0.016	0.003	0.002***	0.013***
	(3.39)	(3.62)	(2.47)	(-1.18)	(-1.61)	(0.29)	(9.32)	(8.85)
Top brokerage dummy	0.640***	0.767***		-0.647***	-0.615***			0.500***
	(3.25)	(3.66)		(-4.27)	(-3.94)			(13.14)
Firm characteristics	Y	Y	Y	Y	Y	Y	Y	Y
Quarter fixed effects	Y	Y	Y	Y	Y			
Broker fixed effects			Y			Y		
Analyst-Broker fixed effects							Y	
No. observations	379680	379680	379665	379680	379680	379665	379266	379680
Test H0: coefficient [HF star analyst] = coefficient [II star analyst]								
(Prob. > chi2)	0.5429	0.4972	0.9094	0.9675	0.9427	0.5901	0.1219	0.817

Table 2.5 Continued

Panel B Multinomial logistic regression (Base group = II star analysts)			
	(1)	(2)	(3)
	Common star vs. II star	HF star vs. II star	Non-star vs. II star
Accuracy score	-0.003	-0.006	-0.015***
	(0.490)	(0.360)	(0.000)
Boldness score	-0.004	0.001	-0.009*
	(0.394)	(0.926)	(0.064)
No. forecasts	0.002**	0.002**	-0.008***
	(0.019)	(0.032)	(0.000)
Analyst experience	0.006	-0.014	-0.058***
	(0.557)	(0.223)	(0.000)
Top brokerage dummy	-0.319	-1.058*	-3.189***
	(0.468)	(0.051)	(0.000)
Percentage of first forecasts	0.509	0.044	2.151**
	(0.589)	(0.967)	(0.011)
Year Fixed Effects		Y	
No. observations		28995	
Pseudo R-squared		0.150	

Note: standard errors are clustered as analyst and p values are in the parentheses.

Table 2.6 Star Analyst Category and Stock Recommendation

This table reports the regression results where dependent variables are analyst-firm level recommendation. The sample includes the recommendation made by analysts during the 12 months prior the end of June in year t (analysts star ranking is released in October year t). Other than the revising analyst, there are at least another analysts made recommendations for the same stock. HF star analyst is 1 when the analyst only appears on hedge funds voted best analyst ranking. Common star analyst is 1 when the analyst is on both HF and II voted best analysts. Leader analyst dummy is constructed based on Cooper, Day, and Lewis (2001). Top broker dummy is one if the broker is among the top 20 largest brokers in a year, based on the number of its affiliated analysts. Size is log of market capitalization. EP is earnings-to-price ratio, Standard errors are clustered at firm level for order logit model and at firm and quarter for OLS model. P-values are in the parentheses.

	Ordered logit	OLS	Ordered logit	OLS
	Rec	Rec	Rec	Rec
HF star analyst	-0.137**	-0.090	-0.160**	-0.084
	(0.021)	(0.100)	(0.045)	(0.287)
II star analyst	0.104	0.074	0.072	0.083
	(0.206)	(0.233)	(0.460)	(0.334)
Common Star analyst	-0.080**	-0.044*	-0.113**	-0.032
	(0.039)	(0.067)	(0.028)	(0.282)
Leader Analyst dummy	-0.020	0.003	0.107*	0.065
	(0.618)	(0.884)	(0.051)	(0.101)
Top broker dummy	-0.282***	-0.154***	-0.402***	-0.208***
	(0.000)	(0.000)	(0.000)	(0.000)
Size			0.067***	0.231***
			(0.000)	(0.000)
Subsequent cumulative 12month ret			0.091*	0.023
			(0.079)	(0.506)
EP			0.195*	-0.077
			(0.068)	(0.317)
Idiosyncratic volatility			-3.714**	-2.747
			(0.039)	(0.159)
Illiquidity			2.098***	0.929***
			(0.001)	(0.006)
Dividend yield			-3.480**	0.321
			(0.028)	(0.123)
External financing			0.548***	0.142*
			(0.000)	(0.052)
Quarter fixed effects	Y	Y	Y	Y
Firm Fixed effects		Y		Y
No. observations	44237	43534	22173	21832
Test H0: coefficient [II star analyst] = coefficient [HF star analyst]				
	Prob. > chi2	Prob. > F	Prob. > chi2	Prob. > F
	0.0130**	0.0031***	0.0596*	0.0159**

Table 2.7 Star Analyst Category and Stock Performance Following the Recommendations

This table reports the regression results where dependent variables are buy and hold abnormal return by trading days subsequent to the recommendation announcement. For example, [0, 1] is the cumulative abnormal return from announcement date to the subsequent one trading day. Value weighted CRSP index is used as the benchmark for buy and hold abnormal return. Δrec is the signed revision of recommendation by an analyst for a given stock (all recommendations included in the sample are active recommendations, and recommendations are considered active within 180 days). Standard errors are clustered at firm and quarter level.

	Buy and hold abnormal return by trading days after recommendation (full sample)								
	[0]	[0, 1]	[0, 2]	[0, 21]	[0, 42]	[0, 63]	[0, 84]	[0, 105]	[0, 126]
Δrec	0.017***	0.020***	0.020***	0.021***	0.022***	0.022***	0.023***	0.023***	0.023***
	(21.99)	(22.32)	(23.24)	(22.44)	(18.73)	(23.07)	(16.73)	(14.52)	(15.62)
HF star analyst	0.001	0.001	0.001	0.002	-0.001	0.001	0.001	-0.003	-0.004
	(0.86)	(0.56)	(0.36)	(0.50)	(-0.42)	(0.14)	(0.08)	(-0.41)	(-0.54)
II star analyst	-0.002	0.001	0.001	0.001	0.001	0.012	0.009	0.001	-0.001
	(-0.68)	(0.31)	(0.23)	(0.36)	(0.11)	(1.23)	(0.92)	(0.06)	(-0.09)
Common star analyst	-0.001	-0.003	-0.003	-0.012*	-0.006	-0.008	-0.010	-0.006	-0.011
	(-0.70)	(-1.28)	(-1.28)	(-2.13)	(-1.34)	(-1.41)	(-1.44)	(-0.85)	(-1.03)
Leader analyst	-0.001	-0.003	-0.003	-0.004	-0.005	-0.003	-0.003	-0.001	0.003
	(-0.68)	(-0.93)	(-1.09)	(-0.95)	(-1.85)	(-1.04)	(-0.68)	(-0.17)	(0.31)
HF star analyst × Δrec	0.004	0.008**	0.007*	0.012**	0.014*	0.009	0.013*	0.013**	0.012**
	(1.78)	(2.46)	(1.99)	(3.01)	(2.15)	(1.35)	(1.99)	(2.38)	(2.81)
II star analyst × Δrec	-0.001	-0.000	-0.000	-0.000	-0.002	-0.003	-0.007	-0.003	-0.004
	(-0.90)	(-0.13)	(-0.04)	(-0.05)	(-0.37)	(-0.56)	(-1.04)	(-0.47)	(-0.73)
Common star analyst × Δrec	0.001	0.003*	0.004*	0.005*	0.005*	0.005	0.007*	0.009**	0.009*
	(1.27)	(2.27)	(2.13)	(2.01)	(1.94)	(1.83)	(2.16)	(2.81)	(1.99)
Leader analyst × Δrec	0.002	0.004	0.003*	0.002	0.004	0.008**	0.009**	0.010**	0.011**
	(1.65)	(1.80)	(1.94)	(1.31)	(1.58)	(2.88)	(2.67)	(2.88)	(2.40)
Quarter fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Broker fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	44190	44191	44187	44112	43896	43637	43350	43088	42831
	Test H0: coefficient [II star analyst × Δrec] = coefficient [HF star analyst × Δrec]								
Prob. > F	0.0493**	0.0331**	0.0488**	0.0759*	0.0122**	0.0494**	0.0248**	0.0255**	0.0061***

Table 2.8 Star Analysts' Recommendation Deviation and Market Reaction

This table reports the regression where buy and hold abnormal returns by different trading days are dependent variables. For example, [0, 1] is the cumulative abnormal return from announcement date to the subsequent one trading day. Value weighted CRSP index is used as the benchmark for buy and hold abnormal return. Deviation is the signed difference between analyst i's recommendation and the consensus recommendation the day before analyst i announcement the recommendation. The consensus recommendation includes recommendations made by other analysts that are active (the most recent recommendation within the prior 180 calendar days). Standard errors are clustered at firm and quarter level.

	Buy and hold abnormal return by trading days after recommendation (full sample)								
	[0]	[0, 1]	[0, 2]	[0, 21]	[0, 42]	[0, 63]	[0, 84]	[0, 105]	[0, 126]
ΔRec	0.015***	0.018***	0.018***	0.019***	0.019***	0.018***	0.019***	0.019***	0.019***
	(24.98)	(29.72)	(29.30)	(21.69)	(13.89)	(11.21)	(7.48)	(5.77)	(5.95)
Deviation	0.004***	0.005***	0.005***	0.006***	0.007***	0.009***	0.010**	0.010*	0.010*
	(6.70)	(6.49)	(6.56)	(6.16)	(5.66)	(3.78)	(2.84)	(2.32)	(2.26)
HF star analyst	0.002	0.002	0.002	0.003	0.000	-0.000	-0.001	-0.006	-0.006
	(1.40)	(1.40)	(1.07)	(0.89)	(0.03)	(-0.06)	(-0.14)	(-0.71)	(-0.72)
II star analyst	-0.002	0.001	0.001	0.001	-0.000	0.011	0.007	-0.000	-0.002
	(-0.92)	(0.22)	(0.17)	(0.29)	(-0.00)	(1.21)	(0.78)	(-0.04)	(-0.22)
Common star analyst	-0.001	-0.002	-0.003	-0.012*	-0.005	-0.007	-0.009	-0.005	-0.009
	(-0.75)	(-1.15)	(-1.12)	(-2.05)	(-1.09)	(-1.28)	(-1.33)	(-0.61)	(-0.85)
HF star analyst × Deviation	0.003	0.006	0.005	0.005	0.005	-0.006	-0.008	-0.012	-0.010
	(1.80)	(1.82)	(1.40)	(1.55)	(1.36)	(-1.36)	(-1.15)	(-1.16)	(-0.94)
II star analyst × Deviation	-0.001	-0.000	0.001	0.002	-0.002	-0.009	-0.014*	-0.011	-0.015
	(-0.25)	(-0.11)	(0.40)	(0.29)	(-0.32)	(-1.19)	(-1.99)	(-1.57)	(-1.43)
Common star analyst × Deviation	-0.000	0.001	0.002	0.002	0.006	0.004	0.004	0.009	0.011
	(-0.14)	(1.05)	(1.78)	(0.74)	(1.26)	(0.91)	(0.85)	(1.66)	(1.86)
Leader analyst dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
Leader analyst dummy × Deviation	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Broker Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
No. observations	44190	44191	44187	44112	43896	43637	43350	43088	42831
Test H0: coefficient [II star analyst × Deviation] = coefficient [HF star analyst × Deviation]									
Prob. > F	0.1939	0.1123	0.3552	0.6567	0.2556	0.8033	0.6336	0.9521	0.7722

Table 2.9 Firm Control Variable Definition

Variable	Definition
Dividend yield	Calculated as the dividend payment of the prior year, divided by the market value of common equity at the end of the prior fiscal year.
Earnings-to-price (EP)	$\frac{\sum_{i=0}^{3} EPS_{T-i}}{P_T}$ EP is the rolling sum of EPS for preceding four quarters, deflated by price at the end of quarter T
External financing	The amount of external financing scaled by the average total assets $= \frac{(SSTK - PRSTKC - DV + DLTIS - DLTE + \Delta DLC)}{(total\ asssets + lagged\ total\ assets)}$
Idiosyncratic volatility	Measured by standard deviation of the residual in Fama French 3 factor regression with three month daily return data
Amihud liquidity (Illiq)	Calculated with the following formula using data over the twelve months preceding the current month $\frac{1}{D_i}\sum_{t=1}^{D_i}\frac{\lvert r_{it}\rvert}{Dvol_{it}} * 1{,}000{,}000$ r_{it} is daily returns and $Dvol_{it}$ is daily dollar trading volume (price x volume) for stock i on day t. D_i is the number of days with available ratio over the twelve months measurement window
Sales growth	$\frac{\sum_{i=0}^{3} Sales_{T-i}}{\sum_{i=0}^{3} Sales_{T-4-i}}$ which is the rolling sum of sales for preceding four quarters over the rolling sum of sales for second preceding set of four quarters and T is the most recent quarter for which an earnings announcement was made a minimum two months prior to the end of quarter q with T >= q-4
Standardized unexpected earnings (SUE)	$\frac{EPS_T - EPS_{T-4}}{\sigma_T}$ the nominator is the unexpected earnings for quarter T, with EPS defined as earnings per share (diluted) excluding extraordinary items, adjusted for stock distributions and the denominator is the standard deviation of unexpected earnings over eight preceding quarters (quarter T-7 to quarter T)

Table 2.9 Continued

Variable	Definition
Institutional ownership	The quarterly shares owned by institutional investors over the total shares outstanding. Observations with greater than 100% aggregate institutional ownership are coded missing.
Volume	First calculate the average (daily trading volume over shares outstanding) during the past six months prior to the end of quarter q, then sort the average daily turnover within the stocks' listed exchange (NYSE,AMEX or NASDAQ) into 100 percentiles (i.e., 0 to 99) and then converted the percentile into 0 and 1 by dividing by 99. Volume is between 0 and 1.

CONCLUSION

In this dissertation, I examine a group of important capital market participants, sell side equity analysts. The first chapter investigates the question: what information do sell side analysts use in their decision process? Specifically, we examine whether sell side analysts are savvy about a group of variables that have been shown to predict future stock returns by academic research. We do not find evidence that sell side analysts in aggregate incorporate such information in their stock recommendation and target price estimates. In the cross section of analyst population, we show that analysts from certain brokerage firms persistently estimate target price in the opposite direction as what return predicting variables from academic research suggests. These results suggest that trading based on investment advice from these brokerage firms could hurt the investment value. We also do not find evidence that “All-star” analysts process this information. However, evidence suggest that analysts’ experience are associated with being anomaly savvy. The second chapter of the dissertation examines the cross sectional differences among “All-star” analysts. Prior studies treat “All-star” analysts as a homogenous group. Motivated by the finding that there are substantial differences among institutional investors, we hypothesize that different types of institutional investors could value different qualities from sell side analysts. Since “All-star” analysts are voted by institutional investors, institutional investor’s preference with respect to analyst attributes is contained in the “All-star” analyst ranking. By comparing the best analysts voted by hedge funds and institutional investors, respectively, we show evidence consistent with the inference that different types of institutional investors value different analyst qualities.

VITA

Haosi Chen was born and grew up in Xi'an, China. She went to Central University of Finance and Economics in Beijing for college. She then decided to study abroad and went to University of Delaware to get a master degree in Finance. At Delaware, she got exposure to academic research through some of the course work and thought analyzing financial data is what she would like to do in the future.

She was very excited when she got accepted to the Finance PhD program in University of Tennessee at Knoxville and worked very hard over the past five years. She is grateful for the opportunity.