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# CONSISTENCY IN ANALYST PERFORMANCE - A COMPREHENSIVE ANALYSIS OF SUPERSTARS

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# 1. Abstract

Sell-side analysts play a prominent role as information intermediaries by converting complex macro and micro information into earnings forecasts and stock recommendations that are widely followed. Yet, extant evidence on the value of analysts' recommendations to market participants is mixed. Although some studies indicate that analyst recommendations do not, on average, yield higher than market returns, other studies document that certain analysts' recommendations help investors earn excess returns. This suggests that some analysts might have superior stock picking ability. Indeed, the popularity of Wall Street Journal rankings which are based on analysts' stock picking ability denotes the significance of analysts' recommendation skills to investors.

A question that naturally arises is whether some analysts have the ability to consistently pick winning stocks and what we can learn from examining their behavior. Motivated by this question, I identify superstars as analysts with relatively consistent stock picking skills and study their attributes. I then evaluate their performance by examining their forecasts characteristics and market reaction to their forecast announcements.

First, I find that experience is an important attribute in the likelihood of an analyst's success as a superstar. However, contrary to prior findings, I document that superstars, on average, are affiliated with smaller brokerage firms. This could be a consequence of the increased analyst regulations during the sample period of 2002-2010. Second, I document superstars' ability to process information as evident from the significant differences in the timeliness (a measure of efficiency in processing new information) and boldness (a surrogate for the information content) of their forecast revisions compared to non-stars. However, their forecast accuracy is not different from that of non-stars, likely due to the tradeoff faced by superstars in providing timely forecasts. Third, market perception of superstars' ability to provide useful information is evident

from the significantly higher price and volume reactions to superstars' forecast/recommendation revisions. Finally, my analyses reveal that, ceteris paribus, superstars tend to follow value firms with high institutional investment. This preference of stock picks may be attributable to the role of brokerage commissions in the post NASD2711 period.

My study contributes to the extant literature on analysts' role in the securities market in several ways. First, I argue and demonstrate that analysts' ability to produce winning recommendations is reflective of their superior information processing skills as evidenced in their forecast announcements. Second, contrary to prior findings, my study highlights that affiliation with larger brokerage houses decrease the likelihood of analyst success. This finding illustrates the impact of increased analyst regulations on larger brokerage houses, suggesting that it could inhibit analysts' ability to provide bold and informative forecasts. Third, my study contributes to the existing literature on analysts' stock preferences and demonstrates the demand for information on stocks with higher institutional holding.

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# 3. Introduction

*"In 2003, S&P rose 28% and the NASDAQ gained 50%. By contrast, the portfolio of a median Wall Street analyst, as judged by recommendations to buy, sell or hold the stock he covers gained just 11% before commissions"*

- Kaufman and Kim (2004).

Indeed, researchers have long questioned the value of analyst recommendations to market participants. Following the crash of 1929, Cowles (1933) documents in his seminal paper "Can stock market forecasters forecast?" that investment decisions based on analyst recommendations do not exceed market returns. Recent studies also document that analysts (buy-side as well as sell-side) do not exhibit the ability to consistently provide winning recommendations. For example Brown and Goetzmann (1995) report that sell side analysts i.e. fund managers' stock picks do not outperform the market. Also, Atinkilic and Hansen (2009) document that analyst recommendation revisions do not have information content and most often "piggyback" on current events.[1]

The findings of this research are surprising given the millions of dollars of annual investment in analyst research, which suggests that, at a minimum, some subset of analysts play a significant role in the capital market (Grossman and Stiglitz, 1980). Dispersion in analysts' recommendations at any given point in time clearly indicates a disparity in their ability to predict future returns on a stock.[2] This lack of consensus implies that consensus recommendation does not have investment value. Although analyst recommendations, on average, may not yield

[1] Market efficiency posits that information is immediately impounded in the share price, thus leaving little or no room for excess returns on recommendations based on public information.

[2] For example, on June 13, 2008, Yahoo's stock had two diverse recommendations: Stifel recommended the stock as a strong buy, Mediamet and Needham recommended it as a hold. The share price dropped from 26 to 23 whereas the volume increased tenfold to 122.5M and 118.5M on June 12th and June 13th respectively compared to 13M on June 11th. Ironically, the stock lost over 50% of its value over the next 6 months despite 3 buy, 11 hold and 7 sell recommendations. Source: I/B/E/S and CRSP files from WRDS.

abnormal returns, the market does value recommendations from select analysts. Identification of such analysts can be of great value to market participants.

In fact, the academic literature documents systematic differences in analysts' ability to process information (Stickel 1992, Sinha et al. 1997, Clement 1999, Jacob et al. 1999 etc.). In particular, Clement (1999) documents the role of experience and brokerage house association on analysts' ability to provide accurate forecasts. Jacob et al. (1999) document a significantly positive association between analysts forecast accuracy and their overall and firm specific experience respectively. Analyst stock recommendations are as important, if not more, for naïve investors as they provide a clear signal to the user towards investment decision. Several studies examine the investment value of analyst recommendations. Their findings indicate that investors could earn excess returns, in some cases as high as four percent, by following the recommendations of a subset of analysts/brokerage firms, indicating that certain analysts have superior ability to identify mispriced securities (Barber et al. 2001, Womack 1996, Bjerring et al. 1983). Womack (1996) examines the returns on recommendations of 14 major U.S. brokerage firms and documents excess returns on their stock picks. Bjerring et al. (1983) on the other hand study the returns on the stock picks of a Canadian brokerage firm and find that their stock picks yield higher returns indicating a superior stock picking ability. This suggests that certain analysts have superior stock picking ability.

Financial press also spends significant resources in the identification of such analysts. These publications employ a unique heuristics to rank analysts performance. For example, Institutional Investor obtains a poll of money managers (buy-side analysts) to identify star (sell-side) analysts. *The Wall Street Journal (WSJ)*, on the other hand, ranks analysts based on the returns on the portfolio of their recommendations. Whereas the *II* rankings could be the result of analyst performance in the current as well as prior years, the *WSJ* rankings are strictly based on a one-year performance evaluation, i.e. prior success/failure is not accounted for. In other words, (inconsistency) consistency in performance is not (punished) rewarded in these rankings, albeit, the heuristic of the rankings could arguably provide motivation for picking risky stocks.

Identification of analysts with ability is very valuable to the market participants. Academic literature as well as financial press has identified outputs such as earnings forecasts or recommendations to identify analysts with ability. Accuracy of earnings forecast is relatively easy to mimic. Indeed, herding has been documented as a common phenomenon in analyst forecasts. Alternatively, returns on analyst stock picks have been employed to rank analyst performance. However, the high returns on becoming a star analyst could encourage aggressive stock picking by analysts. With such aggressive approach, an analyst could become a star and get significant publicity via financial press. Considering such incentives, one could question the ability of rankings in identification of talent. Also, stock picking is a broad signal that may/may not warrant an in-depth analysis of the firm and thus may not represent analyst ability.[3] In sum, it is not clear if analysts with superior stock picking skills also have better information processing ability. The purpose of my study is to evaluate star analysts. Specifically, I address the following questions:

- Can we interpret analysts' relative consistency in providing winning recommendations as superior information processing ability? In other words, do these analysts also provide superior forecasts?
- If yes, does the market perceive these analysts as superstars?

[3] In other words, unlike target price or earnings forecasts, a recommendation is not a point estimate.

- Does experience, access to resources or quantity of workload play a role in the likelihood of an analyst's success as a superstar?
- Can we identify any systematic differences in the stock picks of these analysts compared to an average analyst?

In this study, I address the above questions with three broad objectives in mind. My first objective is to identify analysts who have exhibited relative consistency in their ability to identify winning stocks. Prior literature contends that analyst recommendations could either be a result of their ability to collect and interpret firm/industry-specific information or just a result of following Wall Street 'darlings' based on market indicators such as momentum, growth, volume, etc. (Jegadeesh et al. 2004, Stickel 2007), supporting that analysts' ability to provide winning recommendations does not necessarily reflect their superior information processing skills. Also, one could argue that market efficiency would make it almost impossible for an analyst to pick winning stocks. Yet, prior findings have identified several market anomalies, calling into question the efficiency of the market (Olson and Troughton 2000, Womack 1996). In particular, Womack (1996) documents a drift in the market's reaction to new information which could potentially provide analysts the opportunity to pick under/over-priced securities.[4] Hence, as a first step in this study, I identify "superstars" as analysts who have exhibited relative consistency in their ability to provide winning recommendations to market participants.

The second objective of my study is to investigate whether superstars' stock picking ability can be attributed to their ability to provide superior forecasts. In other words, are their recommendations a result of their ability to process any new information into revising their future expectations about the firm or do their recommendations derive value from market

[4] His finding of an incomplete market reaction towards analyst recommendations suggests either distrust in the recommendations (it could be the case that investors are on the lookout for other confirmatory signals) or their inability to interpret the recommendations.

predictors? Prior literature documents mixed evidence on the association of analyst recommendations and earnings forecasts. For example Jegadeesh et al. (2004) document that analyst recommendations based on market predictors do not provide significant value after controlling for market signals such as momentum, volume etc. Also, Bradshaw (2004) uses analyst forecasts in valuation models and finds that the resultant recommendation is more valuable to investors compared to the recommendation provided by the analyst. Alternatively, Loh and Mian (2006) document that analysts with accurate earnings forecasts also exhibit superior recommendation skills. So, it is not clear that analyst stock picking skills translate to their ability to process information and provide valuable forecasts.

The third objective of this study is to examine whether analyst experience, brokerage house affiliation and portfolio complexity affect their likelihood to be superstars. Related studies have documented that analysts exhibit systematic differences in their ability to forecast accurately (Clement 1999, Jacob et al. 1999).[5] Further, these studies also find that analyst attributes such as experience and size of brokerage house affiliation play a significant role in explaining the difference in analysts' ability to process information. Motivated by their findings, I study these attributes to examine their role in an analyst's likelihood to become a superstar.

To empirically address my research questions, I require a set of analysts with consistent stock picking ability. One way to achieve this is to prepare annual portfolios of analyst recommendations and rank analysts based on the returns on their respective portfolios. An alternate approach is to rely on the *Wall Street Journal (WSJ)* rankings which annually rank analysts based on the profitability of their recommendations. The latter approach has at least two benefits. First, it provides a natural platform to conduct my study as *WSJ* also identifies analysts based on the returns on their recommendations. Second, it eliminates the probability of any

[5] There is an in-depth discussion on these studies in the literature review section

computing errors that may occur in the process of preparing annual portfolios. Therefore, I chose to follow the second method and use the publicly available data from *WSJ*. These rankings, although very popular in the investor community, are also widely criticized by some, who contend that the tournament-type setting of these rankings increases the likelihood of luck in identification of star analysts.[6] This contention is also supported by Bagnoli et al. (2008) who document a turnover of over 85% in the top three *WSJ* stars. The lack of persistence in these ranked analysts' ability to pick stocks suggests that their current/future performance may not be a function of their ability to process information, thereby questioning its perceived benefits (in their identification) to investors. Yet, year after year, *WSJ* outlays significant resources to rank analysts based on their stock picking ability. In addition to the list of ranked analysts, *WSJ* also prints interviews with the top three analysts in each industry. This provides the stars free publicity as well as an outlet to flaunt their stock picking ability thereby improving analysts' future prospects (Groysberg 2010). Such incentives could arguably motivate analysts to pick risky stocks in order to increase their chance at winning. It could be the case that "lucky" analysts as a result could take the winning spot in this race and oust the analysts with superior stock picking ability.[7] Although luck is not sustainable, analysts who "take a chance" at winning oust analysts with ability from being ranked as a star in that year. Despite the likelihood of such events, there are analysts who exhibit repeat success thereby adding considerable value to their ability. Therefore, my sample of "superstars" includes only analysts who have been ranked by *WSJ* at least 3 times over a period of nine years. A detailed discussion on the heuristic is provided in the sample selection section.

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[6] "Since the pros have only one shot to beat the market - there's plenty of incentive to pick risky stocks -The participants tend to pick flaky stocks. The exercise is candidly speculative."-Forbes on *WSJ* stars http://www.forbes.com/forbes/1999/0614/6312301a_print.html

[7] The tournament-type setting of the *WSJ* rankings where "winner takes all" could arguably motivate analysts seeking instant fame to take a chance by picking risky stocks which in part also explains the high turnover in these rankings.

Next, in order to examine the information processing ability of superstars, I compare their annual earnings forecasts with those of other analysts following the same firm during the same period. There has been considerable work on the evaluation of analysts ranked as stars in the *Institutional Investor*'s (*II*) annual rankings of "All American" stars (Fang and Yasuda 2007, Stickel 1992) as well as *WSJ*'s "Best on the Street" stars (Desai et al. 2000). In particular, Desai et al. (2000) study short-term returns on *WSJ* stars' published recommendations in years 1993-1996. Similarly, Stickel (1992) examines the relative forecast accuracy of *II* stars and non-stars for three years. Fang and Yasuda (2007) prepare dynamic portfolios of *II* stars and non-stars over ten years but they designate an analyst as a star only in the year he is ranked as a star. In other words, prior literature on analyst rankings does not examine the persistence in star analysts' ability to provide valuable forecasts/recommendations because it does not follow the same set of analysts over a long period of time.

I add to the prior research on star analysts by examining the *consistency* in the performance of superstars over a period of nine years. Although the process of selection of superstars may appear to indicate their relatively superior ability in that they exhibit repeat success in their ability to pick stocks, it is not clear whether their success in recommendation is a result of their superior ability to process information or their penchant to pick stocks with market predictors such as high momentum/volume.[8] Therefore, an examination of the quality of their earnings forecasts over a period of nine years will shed light on superstar analysts' ability to process information.[9]

[8] Statistically, a random selection from the population of analysts does not identify repeat success of analysts in at least three years.

[9] Recommendations are a broader signal of analysts' sentiments towards the future expectations of a stock. On the other hand, an earnings forecast is a point estimate provided by the analyst and requires indepth analysis of past and present information as well as expectation of the future. Hence, analysis of forecasts is a stricter evaluation of analyst ability to process information.

Prior literature has employed several attributes of analyst forecasts as a measure of their ability to process information (Clement and Tse 2005, Cooper et al. 2001, Mikhail et al. 1999). Motivated by these studies, I analyze the relative efficiency of superstars in incorporating new information in their forecast revisions. Particularly, I examine the characteristics of forecasts of firms that are followed both by superstars and non-stars. By employing a relative method of comparison, I implicitly control for firm-specific variations including a firm's information environment. The three attributes widely used in academic research to measure analyst performance are accuracy, boldness and timeliness of forecast. Forecast accuracy has been widely used as a measure of analyst ability (Mikhail et al. 1997, Clement 1999, Jacob et al. 1999). My results indicate that superstars, on average, have timelier and bolder forecasts compared to other analysts following the same stock, suggesting that the former are relatively more efficient in incorporating new information in their forecasts.[10] The second and third measures help distinguish between lead and herding forecasts. In particular, boldness in analyst forecast revision indicates the divergence from both, the analyst's prior forecast as well as the consensus forecast (Clement and Tse 2005, Gleason and Lee 2003, Trueman 1994). Timeliness, on the other hand measures the efficiency in analyst's ability to process information (Cooper et al. 2001). I employ all these three measures to evaluate superstars' relative ability to process new information. However, this proficiency in processing information may have come at the cost of accuracy which could be the reason that the forecast errors of the two groups of analysts are not significantly different. Alternatively, it could also imply that other analysts recognize the information processing ability of superstars and therefore mimic their forecasts since the

[10] The mean of the response time for superstar analyst forecasts is 2.36 days, whereas that for other analysts is 2.14 days. This difference in mean is significant at 1%

superstars, on average, are documented to be leaders in providing forecast revisions. This could also result in non-significant differences in the forecast accuracy of the two groups of analysts.

Second, I examine the information content of analyst forecast/ recommendation revisions by evaluating the market reaction around their announcements. Analysis of superstar forecasts relative to other analysts provides primary evidence of the differential ability between the two groups of analysts. However, it does not provide evidence on the informativeness of these forecasts. Market participants make investment decisions based on their perception of the value of the information provided by analysts. Therefore, a comparison of price and volume reaction around analyst announcements provides significant evidence on the value of these outputs. Prior literature has corroborated the value of market reaction as a measure of evaluating the information content of announcements (earnings announcement/recommendation changes, etc.). Hence, in order to examine if there are any systematic differences in the information processing ability of superstars and non-stars, I study the market reaction around their forecast/ recommendation announcements. If superstars are indeed efficient in their ability to process information, the market will respond to the revisions in their forecasts/recommendations as evidenced by the price/volume changes around the announcements. Alternatively, if the market does not value the information, I will not find any difference in the market reaction for the two sets of analyst forecasts. Price reactions to incremental information in superstars' forecasts (surprises) as well as recommendations (changes) are significantly higher compared to those of non-star analysts, providing evidence of an incremental reaction to superstar forecasts compared to other analysts following the same firm. Volume reactions also suggest superstars' forecast revisions are relatively more informative. I also conduct portfolio analyses to examine returns on superstar portfolios. Results indicate that, on average superstars' portfolios consistently yield positive returns over a sample period of nine years.

Prior literature has documented that characteristics such as experience, access to resources (brokerage house affiliation), and work load (number of firms/industries followed) contribute to analyst's ability to produce accurate forecasts. In particular Jacob et al. (1999) and Clement (1999) observe that analyst characteristics such as experience, industry specific experience and brokerage house affiliation are significantly associated with ability to produce accurate forecasts. Additionally, Groysberg (2010) documents that access to resources plays a significant role in analyst's ability to perform and achieve star ranking. Hence, in the next set of analyses, I examine the role of experience and brokerage house affiliation in an analyst's likelihood to become a superstar. My findings concur with prior literature on the role of experience in analysts' likelihood to become a superstar. However, contrary to prior research, I find that superstars are more likely to be affiliated with smaller brokerage/ research firms. I attribute this finding to the increased restrictions on analysts affiliated with large brokerage houses enforced by regulations such as RegFD, NASD2711 as well as the Global Settlement.[11] Alternatively, large brokerage houses may implicitly expect affiliated analysts to cover their investment banking clients and also to provide optimistic forecasts for these firms, thus inhibiting their ability to provide valuable information to investors (a similar argument can also be found in Michaely and Womack 1999). I also document that analysts on average follow one or two industries in a given year.[12] Additionally, my results indicate that superstars on average are likely to follow more firms than non-stars.

[11] Note that increased analyst regulations (especially on large brokerage houses/investment banks) led several analysts (George Shapiro, Jeff Hopson, Andrew Neff etc.) to join research firms.
[12] Industry classification is broad (only 10 classifications) and is based on I/B/E/S

Finally, I investigate the firms followed by superstar analysts. Analyses of firm characteristics of superstar stock picks indicate that they prefer to follow value firms with higher market capitalization, block holding and high analyst following.

This study makes several contributions: First, I surmise that despite high turnover in the *WSJ* rankings, analysts with relatively higher frequency in ranking exhibit superior information processing ability. In other words, analyst stock picking ability is significantly associated with the efficiency to process information. I contribute to the extant literature on analysts' role as information intermediaries with an in-depth analysis of superstars over a period of nine years. Specifically, my study corroborates the findings of Loh and Mian (2006) who document that analysts with accurate forecasts also produce profitable stock recommendations. In their study they examine the association between forecast accuracy and recommendations for each firm-year. In other words, for a given firm-year, they evaluate the profitability of recommendations of the analysts in the top decile of forecast accuracy. Whereas their study only examines the association between analyst forecast accuracy and recommendation in a given year, my study analyzes the skills of a set of analysts over an extended period of time.[13] I identify superstars based on their recommendation skills and examine the persistence in their forecast characteristics over a long horizon. I also document that forecast accuracy is not the most important characteristic of superstar forecasts. I find that the superstars assign greater significance to providing more timely and informative forecasts compared to accuracy. I find significant differences in the price and volume reactions surrounding superstar analyst recommendations/forecasts compared to those of other analysts. This suggests that market participants recognize and value superstars' ability to process information. It also suggests that

[13] They do not follow the same analyst over a period of time. In other words, their study does not pertain to the analyses of analyst ability. Second, their study is in the pre-RegFD period when analysts were privy to private information which could result in their superior forecasts /recommends.

timeliness in forecasting is rewarded by brokerage commissions which could potentially be the driving factor in superstars' decision to tradeoff accuracy for timely forecast revisions.

Prior studies have documented mixed findings with regards to value of analyst recommendations. Whereas some studies suggest that analyst recommendations have value (Jegadeesh et al. 2004, Barber et al. 2001, Bjerring et al. 1983), others find evidence to the contrary (Atinkilic and Hansen 2009). To the best of my knowledge, this is the first study that identifies superstars and examines the *consistency* (emphasis added) in their ability to process information. Focusing on a specific set of sell-side analysts over a period of nine years has distinct advantages compared to recent studies on value of analyst recommendations. First, analysis of their outputs over an extended period of time establishes their superiority in processing information compared to an average analyst. Second, it helps identify systematic differences in superstar characteristics compared to an average analyst. In other words, I identify significant analyst characteristics that increase the likelihood of his/her success in the capital market. Prior studies have linked analyst characteristics and their ability to perform (Clement 1999, Mikhail et al. 1999, Jacob et al. 1999) but these studies have not examined the persistence of those characteristics. Finally, examination of their stock picks provides an insight into superstar analyst preferences. Overall, the study helps answer the most important question of what it is that makes analysts maintain their superiority in an efficient and competitive capital market. Also, I extend the findings of prior literature by providing a heuristic to identify a set of analysts with superior ability.

Prior literature has provided significant insight on the published analyst rankings by evaluating the ranked analysts' ability to provide superior forecasts/recommendations. For example, Desai et al. (2000) examine the returns on published recommendations of *WSJ* stars and find these stocks yield significantly higher returns compared to firms from the same industry and of similar size.[14] Fang and Yasuda (2009) and Stickel (1992) examine the recommendations and forecast accuracy respectively of the "All American" stars published by the *Institutional Investor* and document that the stars exhibit superior performance in the year prior to becoming star as well as in the year they become stars. Specifically, Stickel (1992) also documents that the stars performance deteriorates in the year before he loses his membership in the rankings. In summary these studies do not identify superstars and examine their performance over an extended period of time. If the star loses his status as a star, he/she is no longer included in the sample. Also, the majority of prior studies with the exception of Desai et al. (2000) use the *II* star sample.[15,16]

Unlike prior research, I identify superstars from the *WSJ* rankings and analyze their ability over a period of nine years regardless of their brokerage association. The nine-year sample period includes the years during which the analysts may not be ranked as stars.

The rest of the paper proceeds as follows. I discuss the motivation and develop hypotheses in the next section. Section three describes the sample selection process and section four discusses the research methodology. In the fifth section I discuss the results and the final section has conclusions and prospects for future research on the subject.

[14] The WSJ publishes interview with top three star analysts. In this interview, the analysts provide names of their current stock picks. Desai et al. use these stock picks for their analyses of star analysts' ability to recommend – almost similar to examining a self fulfilling prophecy.

[15] There are many advantages of using the II – All American Star analysts as a sample. The most significant of it is the stickiness of the sample. Unlike WSJ stars, the II stars have a low turnover and since their selection is based on a poll of buy-side analyst, they tend not to lose their rank unless they shirk leading to a decrease in quality of service or they become buy-side analysts.

[16] Groysberg et al. (2011), Fang and Yasuda (2005), Bagnoli et al. (2008), Desai et al. (2000) and Stickel (1992)

# 4. Related Literature

Sell-side analysts' contribution to the securities market has been a topic of considerable research in Accounting and Finance. Although the research depicts mixed findings on the value of analyst recommendations on average, they recognize analysts' contribution towards market efficiencies. Schipper (1991) and Ramnath, Rock and Shane (2008) provide a detailed review on research in this area. Particularly, in her commentary on analyst forecasts, Schipper (1991) calls for the need to go beyond the examination of statistical properties of analyst forecasts. She urges researchers to examine these forecasts in context of analysts' recommendations.

In this study, I take a subset of analysts and examine the link between their ability to recommend and their information processing skills. The research on sell-side analysts is extensive so for the sake of brevity, I discuss a few papers relevant to my study.

*4.1 Analysts' Recommendations:*

Cowles (1933) can be credited as a seminal study investigating the value of analyst recommendations. In his paper, he studied over 7,500 recommendations from 45 professional agencies and documents that the returns on their stock picks are lower than market returns. Barber, Lehavy, McNichols and Trueman (2001) prepared portfolios of analysts favorites (stocks with most buy-recommendations) and least favorites (stocks with most sell recommendations) and found that a trading strategy that goes long (short) on the most (least) favored stocks would yield excess returns greater than 4%. However, their strategy required a daily rebalance which ate up all the profits from such a portfolio. On the other hand, Jegadeesh, Kim, Krische and Lee (2004) warn investors not to naively follow analyst recommendations. Their study documents that consensus analyst recommendations do not contain incremental information given other predictive signals such as momentum and growth. They argue that whereas some analysts recommendations are provided after in-depth analyses, others are "tilting towards stocks with particular characteristics that predict future value" (page 1084, para 2). Buy recommendations that are in concurrence with momentum or contrarian signals tend to outperform stocks that are less favored by the analysts whereas stocks with less favorable predictive signals underperform. Hence the authors conclude that market signals have more predictive value than some of the analyst recommendations. In the same vein, a recent study by Atinkilic and Hansen (2009) dismiss the ability of analysts to provide valuable recommendations and argue that these recommendations usually "piggyback" on recent news/ information events. In particular, they examine analyst recommendation revisions and document that the returns on stock before revision is significantly large (-3.7% before downgrades and 1.1% before upgrades) and argue that the post revision returns can be explained by the pre-revision returns. In other words, analysts simply ride the wave created by new information.

Analyst recommendations have also been documented to be positively biased, especially for the clients of the investment banking firms. Michaely and Womack (1999) examine the credibility of recommendations by affiliated analysts and document that not only these analysts issued over 50% more buy compared to sell/hold recommendations, the stocks recommended by these analysts performed worse than those recommended by non-affiliated analysts. Lin and McNichols (1997) also document that underwriter analyst issue significantly more buy recommendations than other analysts. Barber, Lehavy, McNichols and Trueman (2007) compare returns on buy recommendations of affiliated analysts with research firm analysts and document significant superior performance of the latter. However, the results are reversed for sell/hold recommendations implying that market adjusts for the optimistic bias in affiliated analyst recommendations. In summary, prior literature has documented that average analyst recommendation does not provide significant investment value to market participants. Yet, several studies document that a subset of analysts have the ability to provide recommendations that generate excess returns. In particular, Bjerring, Lakonishok and Vermaelen (1983) evaluate the recommendations of a Canadian brokerage firm and document significant excess returns on their stock picks (even after accounting for brokerage commissions). Also, Womack (1996) examines recommendations from 14 major U. S. firms and documents a significant positive return. He also evaluates the market reaction over an extended period (six months) and finds a significant drift for both buy and sell recommendations. He concludes that the market reaction is incomplete and that investors as well as analysts can identify mispriced securities due to this incomplete reaction.

*4.2 Analysts' Attributes and their performance:*

Prior studies have documented systematic differences in analysts ability to forecast accurately. Further, these studies have found that these differences are significantly associated with analysts' experience, their brokerage house affiliation as well as number of firms followed by them. In particular, Clement (1999) attributes the differences in analysts' forecast accuracy to their experience, size of the brokerage house affiliation and the portfolio of firms followed. He documents significant positive association between forecast accuracy and experience as well as access to resources (measured by the size of the brokerage house affiliation) whereas an inverse association with the number of industries followed (a measure for the complexity of work load) followed by the analyst. However, argue Jacob, Lys and Neele (1999) that although experience may be associated with analyst performance, it is analyst's innate ability that begets his success in providing accurate forecasts. They perform a host of analyses and confirm that forecast accuracy is associated with analyst aptitude, his relation with the firm as well as access to resources but is not improved further by analyst experience.[17] In a recent study, Cooper Day and Lewis (2000) rank leader analysts based on the timeliness of their forecast announcements. They document that forecast announcements of leader analysts thus identified have greater impact on the market. They also examine the performance of these leaders and document their forecasts to be significantly more accurate compared to average analyst. These studies suggest that the analyst population includes a subset of analysts with the ability to provide informative forecasts/recommendations.

### *4.3 Star Analysts:*

Hence, it is possible to identify analysts with superior skills within the large population of analysts. Indeed the financial press annually employs significant resources in identifying star analysts. Although there are several rankings available to investors, the two highly popular rankings are from *Institutional Investor's* "All American Star" ranking and the *Wall Street Journal's* "Best on the Street" ranking. The heuristics employed by these two rankings are starkly different leading to diverse outcomes. Whereas the *II* rankings use a survey method, the *WSJ* strictly applies a quantitative approach of ranking analysts based on the annual returns on their recommendation portfolio. Due to the difference in methodology, the turnover in II rankings is significantly lower compared to the WSJ rankings.

Extant literature has provided several studies related to star analysts ability to perform. In particular, Stickel (1992) examines the forecast accuracy of *II* stars before and after they appear in the rankings. His results suggest that analysts with superior ability to provide accurate

[17] Both these studies measure forecast error as analyst forecast error compared to average forecast error. In other words, the measure is relative and not absolute measure of analyst's ability to provide accurate forecasts.

forecasts are more likely to become stars. He also documents that stars lose their rankings if their performance (forecast accuracy) deteriorates. He also studies market reaction to forecast surprises of *II* stars and documents significant price reaction suggesting that investors value the information provided by ranked analysts. In the same vein, Fang and Yasuda (2007) also document significant investment value in *II* star analysts' stock recommendations. A recent study by Bagnoli, Watts and Zhang (2008) examines the persistence in analyst rankings pre- and post-RegFD.[18] Their results indicate that *II* stars experience a significant increase in turnover during the implementation years of RegFD but this increase is documented to be short-lived and the levels return to pre-RegFD period in a few years. The turnover in *WSJ* rankings, on the other hand remained significantly high (unchanged) at 85% in all the years covering a period from 1998-2003. Indeed, the authors argue, it is difficult to "maintain a competitive edge" in a stock picking tournament such as the *WSJ* rankings attributing to the inability of *WSJ* rankings to identify stars. Yet, Desai, Liang and Singh (2000) document that the stock picks of the top three stars in each industry identified by the WSJ rankings perform significantly better than the benchmark (size and industry) stocks. The authors employ a buy and hold (over 10 to 500 days) methodology to compare the returns on the star stock picks and the benchmark stocks identified as stocks similar in size and industry. They conclude that stars demonstrate a superior stock picking ability. Emery and Li (2009) also examine the performance of the *WSJ* and *II* stars and document performance to be a more important determinant in the former rankings compared to the latter. They also find that the performance of *WSJ* stars is significantly worse in the years

[18] Regulation FD (RegFD) was intended to level the playing field for all the market participants. Hence, it prohibited company managers from privately disclosing any information to analysts. This in turn affected the analyst's who curried favors with managers to obtain private information thereby reducing their ability to provide information to money/hedge fund managers. This in-turn would affect their ability to be considered favorably for the purpose of the rankings.

following their appearance in the rankings. They find no evidence of the analysts' ability to provide recommendations that yield excess returns.

### *4.4 Persistence in analysts' performance:*

Persistence in analyst performance has been examined for the buy as well as sell-side analysts. For example Brown and Goetzman (1995) evaluate the performance of mutual funds and document the persistence of relative risk-adjusted returns. However, the authors find that this result is mostly attributable to funds that lag S&P 500. Studies that examine persistence in sell-side analyst performance include Sinha, Brown and Das (1997), Mikhail Walther and Willis (2004) and Li (2005) Sinha et al. (1997) document that analysts exhibit persistence in their ability to provide accurate forecasts. They use percentile rankings to identify analysts as superior or inferior in a given estimation period. They find that the superior analyst maintain their superiority in the holdout period whereas inferior analysts exhibit improvement in performance. They interpret these findings as analysts' ability to maintain/improve performance over time. Mikhail et al. (2004) document that analysts whose recommendations earn higher (lowest) returns continue to provide high (low) returns in the consecutive periods. They employ three windows (-2, 2), (-2, 20) and (-2, 60) to measure returns on analyst recommendations. They sort analysts deciles based on these returns and examine the returns on analysts in the top and bottom decile. They document a significant positive association between the past and future performance. The authors interpret this finding as persistence in analyst's stock picking ability. In the same vein, Li (2005) documents persistence in analyst recommendation. The author ranks analysts based on risk adjusted returns on their recommendation portfolios. Persistence is measured as the correlation between differences in analyst performance in the two periods; estimation and holdout. The regression of the returns in holdout period on preceding estimation period provides evidence of persistence in performance. To summarize, majority of the prior studies that examine persistence in performance evaluate analysts' ability to perform in consecutive periods. To the extent that success begets success, these results are not surprising. A real test of analysts' persistence in performance would be to examine their performance over a longer period of time. To that extent, my study contributes to the literature by evaluating analyst performance, relative to their peers (average analyst) as well as the market (ability to provide excess return to investors).

# 5. Motivation and Hypotheses Development

Sell-side analysts' stock picking ability has been widely debated in academic literature and financial markets. In fact, dispersions in recommendations are a clear indication that only some analysts will be correct in their predictions. Although, proclaims Barber et al. (2001), a strategy to go long (short) on stocks with highest buy (sell) recommendations will earn an overall return of 4%. However, these profits are lost after brokerage commissions are accounted for. Other studies such as Brown and Goetzman (1995) also document the inability of buy-side analysts' investment strategies to surpass market returns. . In fact, a contrarian strategy suggests Barber et al. (2003) yields excess returns. They document an average annualized excess return of -7.06 (13.44) percent in the years 2000 and 2001 on stocks most (least) favored by analysts. More recently, Atinkilic and Hansen (2009) study the change in recommendations and find that these changes are usually led by recent news. They document an economically insignificant price change associated with these revisions. However, studies have identified analysts with the ability to provide winning recommendations. For e.g. Bjerring et al. (1983) document that following the recommendations of a Canadian brokerage house would yield significantly positive abnormal returns. Womack (1996) studies the value of recommendations from 14 large U.S. brokerage houses and documents a excess returns that continue to persist for six months.

So, it must be the case that there are analysts with superior stock picking ability. The question is whether their recommendation skills are a result of their ability to process information. Jegadeesh et al. (2004) argue that analyst recommendations could be based on their investigation of firm's expected value based on their expectations of firm's future earnings or it could be based on their ability to interpret market predictors. Indeed, Bradshaw (2004) finds that recommendations based on analyst forecasts are more accurate than analysts' recommendations *per se*. An alternate evidence provided by Loh and Mian (2006) attest that analysts with accurate forecasts also have better recommendations suggesting that the forecasting ability of analysts translates into their recommendation skills. So, in summary it is not clear that analyst recommendations are in effect a product of their forecasting ability. In my study, I address this issue by examining the forecast properties and attributes of superstars defined as analysts with consistent success in their stock picking ability.

One way to identify such analysts is a careful evaluation of their stock picks each year. Another way is to utilize the rankings of *WSJ* where analyst rankings are based on their stock picking ability so it provides a natural platform to identify superstars. The data selection section provides a detailed discussion on these rankings. The *WSJ* rankings are solely based on analysts' stock recommendations in a given year. An analyst gets no credit for success in other years. In other words, it's a quantitative analyses of portfolios prepared on each analyst's recommendations in a given calendar year. Such a methodology could motivate analysts to take a chance towards become popular by picking risky stocks. This in part also explains the high turnover in the rankings supporting critics' claim on its perceived benefit to market participants.[19] Liang et al. (1995) also document that the pro picks earned higher returns in the short run (2 weeks) but the random picks did better in the longer run (six months). However, Desai et al. (2000) compare returns on pro picks with stocks similar in size and industry and document that the former outperforms the latter. In summary, it is not clear whether the *WSJ* stars are superior in their ability to process information compared to an average analyst.

Since the focus of my study is to examine analysts who have exhibited persistence in stock picking ability, ideally, my sample of superstars should include analysts who have appeared in

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[19] In fact, to address the debate on the value of its annual rankings, *WSJ* launched a monthly publication of "Investment Dartboard" column where both random as well as professional picks were announced. The result: Pro picks performed better than the random picks.

the rankings each year. However, this imposes a serious restriction on the sample size so I include all the analysts with at least three winnings. I provide an in-depth discussion on these tradeoffs in the next section. Although analysts who have exhibited the ability to pick winning stocks at least three times in a period of nine years are likely to be better than an average analyst, it is not clear if the success is attributable to their ability to process information or their preference to pick momentum/volume stocks. Therefore, a prudent approach to examine if the superstars have skills to process information would be to examine the quality of their outputs. Hence in the first set of hypotheses, I assess the forecast properties of the sample of superstars.

*5.1 Test of ability:*

Significant amount of time and resources go into estimation of a firm's annual forecasts. These forecasts are continuously revised to adjust for any new information regarding the firm, its competitors or their industries. Whereas analysts' recommendation, a broad signal of stock's future value, is based on long term conjectures about the firm and its environment, their forecast, a point estimate, is based on short term performance of the firm. Annual forecasts are a key in valuation of a firm which in turn may warrant a change in existing recommendation for a firm. Analysts' ability to provide valuable forecasts has been considered paramount in their evaluation as well as future prospects. Indeed, higher forecast errors compared to peers could cost an analyst his career (Mikhail et al. 1999). Moreover, studies also indicate that analysts' reputation is also significantly associated with their ability to provide valuable forecasts (Stickel 1992). A prime reason for herding in analysts behavior is their inability to provide accurate forecasts. Since forecasts are so important, certain analysts chose to mimic the forecasts of reputed analysts. Forecast characteristics have been widely used in academic literature as a measure of analysts' performance (Clement 1999 and Jacob et al. 1999) Studies such as Cooper et al. (2000)

identify leader analysts based on the timeliness of their forecast announcements. Additionally, Trueman (1994) and Hong et al. (2000) distinguish leader analysts from herders based on the boldness in their forecasts They contend that lead analysts differentiate themselves from average analysts by providing bold, in other words, more informative forecasts. So, in order to evaluate examine superstar analysts ability to process information, I compare their forecast characteristics in relation to other analysts following the same security.

*a. Forecast Characteristics:*

Timeliness: It is a widely known fact that trading commissions have a significant influence on analyst compensation. Therefore, it is important for an analyst to provide valuable information to their clients which would turn into investment decision leading to brokerage commission for his firm. A majority of trading volume comes from investment banking firms who in turn get information from a host of brokerage houses. For an analyst to capture the trading volume, he is must provide timely as well as valuable information to the money managers. This signifies the importance of efficiency in processing new information in order to provide revised forecasts. An analyst who can quickly incorporate new information in his/her forecasts reaps the benefit of the revenue created as a result of the trade associated with that new information. Indeed, Cooper et al. (2001) document that lead analysts identified based on timeliness of forecasts have a greater impact on the market in terms of price and volume. A timely forecast denotes analyst confidence in his/her ability to process information. So, I use timeliness (age) of forecast as my first measure to evaluate whether *superstars* demonstrate relatively superior ability to process new information and produce revised forecasts. To the extent that these analysts have superior ability to process information, their reaction to new information is expected to be timelier i.e., their forecast revisions will be quicker compared to other analysts. Using timeliness as my first yardstick to measure the ability of the star analysts, I propose the following hypothesis (stated in alternate form):

*H1A –Superstars are timelier in revising their forecasts in response to new information.*

Boldness: Analysts ability to provide timely forecasts *per se* has little or no value. If it did, analysts would just revise forecasts to create trading volume. Such a strategy would not work as the value of the forecast is only as good as the extent of new information it provides to the market participants. Hence, in addition to timeliness of forecast, it is pertinent to examine the information content of the revised forecasts. Using a model Trueman (1994) predicts that analysts with ability will be less influenced by prior forecasts; in other words, these analysts are more likely to announce bolder forecasts compared to an average analysts. When analysts with superior information processing skills revise their forecasts, they are more likely to provide significant information in the revisions. Also, their confidence in their ability will be reflected in their revision. Empirical studies have also documented the significance of bold forecasts to market participants. Particularly, Clement and Tse (2005) find a significantly positive association between prior forecast accuracy and current boldness in forecast indicating that prior forecast accuracy instills confidence in analysts which in turn is portrayed in the boldness of their future forecasts. Gleason and Lee (2003) also show that bold forecast revision (those that diverge from consensus) command a greater market response in terms of price change. Hence, if superstars are indeed super in their ability, their forecasts will be bolder than the consensus forecasts. I test this conjecture in the following hypothesis (stated in alternate form):

*H1B– Superstars provide bolder forecasts compared to other analysts following the same security.*

Accuracy: Forecast accuracy is considered paramount characteristic in the measure of analyst performance. Indeed, majority of academic studies use analysts' ability to forecast accurately as a measure of their performance (Clement 1999, Sinha et al.1997, Stickel 1992). In particular, Stickel (1992) documents that analysts with greater forecast accuracy are more likely to be selected as star analysts in the *II* survey and the selected analysts are more likely to lose their position if their forecast accuracy decreases. This suggests the significance of forecast accuracy to the buy-side analysts who influence the *II* polls. In fact, Mikhail et al. (1999) document that analysts' performance is measured in terms of their ability to provide accurate forecasts compared to their peers. Inability to do so could be considered one of the prime reasons for analysts to lose their jobs. They examine the relation between forecast accuracy and analyst turnover and find that analysts (who contribute forecasts to the Zacks database) are more likely to change brokerage firms or leave the database altogether when their forecast accuracy is lower relative to their peers. They find that the profitability of analysts' stock recommendations is unrelated to analyst turnover, suggesting that analysts may have more of an incentive to issue accurate forecasts than to provide profitable stock recommendations. Cooper et al. (2001) use analyst forecast accuracy as one of the measures to identify lead analysts. They find a positive and significant market reaction to the forecasts of lead analysts thus identified. Also, Loh and Mian (2006) provide evidence of profitable stock recommendations from analysts who have more accurate forecasts indicating that the analyst ability to forecast reflects in his stock recommendations. Stickel 1992 interprets a positive association between star analyst forecasts and stock returns as ability of star analysts. Analyst performance evaluation also includes their ability to forecast accurately. Hence I use accuracy as another measure to examine the processing ability of my sample of superstars and propose the following hypothesis (stated in alternate form).

*H1C– Superstars can forecast future earnings more accurately than other analysts.*

*b. Market Perception of Superstar Forecasts/Recommendations:*

Analysis of superstar forecasts relative to the forecasts of an average analyst provides a relative inference of superstars' ability to process information compared to his/her peers. However, it does not provide any indication on the relative superiority of their forecasts in terms of its information content as well as value to the investors. Therefore, it is imperative to examine the market response to their outputs. Hence, I take support of the efficient market hypotheses to examine the relative value in superstars' forecasts/recommendation revisions. In particular, I examine the price and volume reaction surrounding the announcement of their forecast/recommendations.

Anecdotal evidence suggests that some successful analysts (stars) use their reputation for personal gains and mislead investors with optimistic forecasts.[20] However such behavior is not sustainable in the long term. Hence, market reaction over all the years in the sample would provide substantive evidence to the analysis of ability in the superstars. If these analysts possess better processing skills, their forecast/recommendation announcements will warrant significant market reaction and impact the actions of other analysts. Hence, I surmise that the analysis of superstars' ability would be incomplete without examining the market reaction and the reaction of other analysts to their announcement. Moreover, if these analysts do indeed have superior stock picking skills, their stock-picks would not only provide excess returns in the years they are

[20] In two cases decided by National Association of Securities Dealers arbitrators last month, people who lost money investing in WorldCom Inc. stock based on Mr. Jack Grubman's research were able to secure awards against both Citigroup and its former *star analyst*.- WSJ Jan 12, 2005. p. A.1

ranked but also in the long run. Ideally, I would like to compare the returns of their portfolio with the other analysts' portfolios but that exercise would be futile considering the sample comes from *WSJ* rankings where this methodology is applied to identify stars. On the other hand, short term market reaction to their announcements would provide substantive evidence (market's perception) of their ability. An alternative explanation that the *superstars* could exploit their lead positions by recommending firms from which they receive rents through investment business is also feasible. However, there are two reasons why this may not be the case for my research design: first such act may not be sustainable over a long period and second, these analysts are not ranked each year. They have exhibited success at the rate of only 34%. So, one indication of information processing ability is to examine market reaction to change in analyst recommendations. And if the market recognizes the ability of these analysts, it will react more strongly to their recommendations compared to those of other analysts. Therefore I test the following hypothesis (stated in alternate form):

*H2A –Market response is significantly higher for changes in superstars' recommendations.*

Although recommendation provides a clear signal towards an investment decision at the market price, it is a very broad signal towards analysts' expectations of future returns on the stock. For instance, a stock with current price of $10 would have a strong (buy) recommendation if the expected future price is any value greater than the current price. Earnings forecasts, on the other hand, require a deliberate effort in analyses of future expectations of a firm's performance. Hence, analysts are more often evaluated on their ability to provide valuable properties of their forecasts. Indeed, prior literature has documented the superiority of analyst earnings forecasts over recommendations. In particular, the findings of Bradshaw (2004) suggest that analysts' earnings forecasts are more informative than their recommendations; investment decisions based on analyst earnings forecasts in a valuation model yield higher returns than consensus recommendations. On the other hand, Loh and Mian (2006) document that analysts' ability to provide accurate forecasts is also reflected in their stock recommendations.[21] Therefore, an examination of the market's reaction to the information content in analysts' forecast is imperative (also see Mikhail et al. 2001). This leads to the second hypothesis in the market study (stated in alternate form):

*H2B – Market reaction is significantly higher for earnings forecasts of superstars.*

*5.2 Analyst Characteristics:*

Granted that the survival in the role of analyst in itself is a challenge given the competition and demands of the brokerage houses as well as their clients, there are differences within this population. If not, all the forecasts/recommendations would be in complete harmony. In fact, related studies have identified certain characteristics that distinguish analysts with superior ability from an average analyst (Clement 1999, Jacob et al. 1999). However, results are mixed on the association between analyst experience and his ability to process information. Whereas Milkhail et al. (1999) and Clement (1999) document that analysts firm specific experience is significantly correlated to his/her forecast accuracy, Jacob et al. (1999) provide evidence otherwise. In their study, the authors argue that analyst aptitude matters more than his/her experience. Contrary to contemporary studies, they document that once analyst aptitude and brokerage house affiliation are controlled for, there is no significant association between experience and analyst ability to produce accurate forecasts. In this competitive market only analysts with a certain minimum aptitude are able to sustain for a longer period of time. Hence, I

[21] Indeed in my conversation to a few analysts, I learned that although recommendations are a clear signal, it is not the change in recommendation that creates price reaction but the reason leading to the change.

conjecture that experience plays a significant role in creating superstars. My hypothesis stated in alternate form is:

*H3A – Experience increases analysts' likelihood to being a superstar.*

Analysts' ability to provide accurate forecasts has also been shown to have significant association to the brokerage house affiliation of the analyst (Clement 1999, Jacob et al. 1999). The authors argue that employment with larger brokerage houses not only guarantees access to more information (including access to private information from current and future clients of investment banking division) but could also imply more assistance from junior analysts which could in turn be reflected in their forecasting ability. In other words, it could be the case that the success of analysts as information processors could be partly attributed to the brokerage house affiliation. Alternatively, affiliation with large brokerage houses could also inflict optimistic bias in analyst outputs (Barber et al. 2007, Lin and McNichols 2007). So, although size of the brokerage house could help analyst get management access, such affiliation could also in turn hinder analysts' ability to publish accurate forecasts.[22] However, affiliation with large brokerage houses has significantly more benefits compared to the associated costs. In fact, empirical evidence suggests that optimism in earnings forecasts is not limited to analysts associated with large brokerage houses, albeit it is significantly associated with analysts' penchant to curry favors with management (Das et al. 1998). Hence, by and large, association with larger brokerage houses has relatively higher benefit towards analysts future performance. This leads to my next hypothesis on the role of brokerage house affiliation on analyst performance (stated in alternate form):

[22] For example UBS fired their analyst, Chung Chu, after he issued a sell recommendation on Enron http://www.chron.com/CDA/archives/archive.mpl/2002_3524570/analyst-firing-came-after-advice-to-sell-enron-sto.html

*H3B– Size of brokerage house affiliation improves the likelihood of an analyst to being a superstar.*

Generally speaking, the work load (quantity and complexity) is likely to impact the quality of output in any profession. One would expect that an analyst who follows more (less) number of firms would be able to devote less (more) time on each firm. Therefore, the quality of final product may be significantly different. However, in this day and age of complex computing algorithms, such a comparison may not be accurate. One has to account for the technology difference in these analysts' processes. The benefit of following more firms is that the analysts can cater to a broader clientele which in turn increases the brokerage revenue. However, analysts with superior stock picking ability can afford to focus on select firms and provide significant information to their clients. Indeed Clement (1999) documents a significantly negative correlation between the forecast accuracy and the number of firms followed. I conjecture that analysts with significant confidence in ability would prefer to follow less number of firms in order to enable them to provide superior forecasts. Therefore, my hypothesis (stated in alternate form) reads:

*H3C –Superstars are likely to follow fewer firms compared to average analysts.*

In the same vein, I also investigate the effect of portfolio complexity on analysts' performance. Prior findings suggest that portfolio complexity, i.e. following more industries has a negative effect on analyst performance. Superstars are more likely to be industry experts, in that their portfolio of firms is not spread across several industries. Hence, my hypothesis, stated in alternate form is:

*H3D – Compared to an average analyst, superstars are more likely to be industry experts.*

*5.3 Superstar Stock Picks*

Incentives such as brokerage commissions, access to private information etc. play a considerable role in analysts' decision to follow a certain stock. Clearly, limited resources constrain their ability to follow more stocks so analysts have to be prudent in their stock picks to ensure that their effort is well rewarded.

Therefore, I evaluate the firms followed by superstars compared to those followed by other analysts. This exercise is necessary for two purposes: First, it would be interesting to examine if superstar stock picks are consistent with the anomaly literature. Second, and more importantly, it will provide an insight on the role of incentives in the superstars' stock picks. In particular, I investigate whether superstars are more likely to follow firms where their research can provide significant value, in other words, would their expertise in processing information be more valuable for firms where acquisition of new information is difficult or are they more likely to pick larger firms that would denote greater potential for brokerage commission? These questions are important to understand how analysts are able to sustain their success in such a competitive market. Therefore, I examine the characteristics of superstar stock picks in relative to other analysts stock picks. Mainly, I study the following stock characteristics.

<u>Firm Size:</u> Prior literature has provided significant evidence on the importance of brokerage commission to analysts' current and future prospects. Indeed, most brokerage firms analysts' compensation is related to the trading volume related to his/her forecasts. In that regard, firm size is a significant consideration for the analysts. However, it is not entirely a clear choice as larger firms have lower information asymmetry which leaves less room for new information that would lead to trading. Studies have documented that return to information is higher for firms with higher information asymmetry (Lobo et al. 2009, Barth et al. 2001, Cooper et al. 2000 and Li et

al. 2009). In particular Li et al. (2009) document that analysts with skills differentiate themselves in the market by following firms that are more difficult for other analysts to follow.

Analyst Following: Prior research has documented higher analyst following in firms that are larger in size (Bhushan 1989) as well as firms with more disclosures, i.e. firms with higher information transparency (Lang and Lundholm 1996). This suggests that firms with lower information asymmetry are easier to predict and thus draw greater analyst following. However, higher number of analysts following a firm also implies an increase in the information environment of the firm and thereby a decrease in rents for these analysts following the firm. Indeed, prior literature has documented a decrease in the information asymmetry (a measure of firm's information environment) with increase in analysts following. Also, Ayers and Freeman (2003) document that firms with higher analyst following are more efficiently priced (in other words, the price reflects future earnings sooner compared to firms with lower following). Based on these findings, it could be argued that an analyst with superior ability would follow firms with higher information asymmetry (i.e. lower analyst following). However, if the motivation to follow a stock comes from the related brokerage revenue, superstars would be expected to follow large firms with apparently have higher analyst following. Also, if superstars are efficient in processing information, they can yield higher returns by following larger firms.

Institutional Holding – Analysts largest and most lucrative clientele are the large investors such as money managers, institutional investors, etc. Analysts cater to these clients in terms of providing research analyses on firms as well as any new information regarding their investments. Hence the analysts, especially superstars, are more likely to follow firms with higher institutional holding.

Value Stocks: The value v/s glamour anomaly asserts that value (high book-to-market) firms have more investment value compared to glamour (low book-to-market) firms which tend to be overpriced. Also, institutional investors also prefer value versus glamour firms so if the intent is to identify mispriced security in order to provide value in the recommendations as well cater to the institutional investors, the superstars are more likely to follow value firms. So, I compare the book-to-market value of the firms followed by superstars with other analysts.

# 6. Sample Selection

To conduct my study, I require a set of analysts who have consistently exhibited superior skills to pick stocks. This would require ranking analysts based on the returns on their recommendations. Or, I could use the annual rankings published by the *WSJ* as they apply similar heuristic in their annual recognition of stars. I select the latter approach and examine the *WSJ*'s annual "Best on the Street" publication from 2003-2011.[23]

In order to fully understand the implication of the data on my study, a discussion on the *WSJ* rankings is warranted here. The *WSJ* annually ranks sell-side analysts based on the performances of their portfolios of stock recommendations.[24] This list is published each year in the month of April/ May in the *WSJ* and lists the ranking based on prior year portfolio return. Every year the survey focuses on approximately 44 industries that *WSJ* believe to be of interest to the investors. Although there are minor changes in industry identification each year, most of the major industries appear every year. Industries included in the survey for the year 2010 ranking are

[23] One way to identify superstar analysts is to evaluate the returns on a portfolio based on their recommendation in a given year. Another way to identify superstars is to use the annual rankings published by *WSJ*. I chose to use the second method for a couple reasons: first and foremost is that *WSJ* uses analyst recommendations to identify stars each year and second, the stars identified by the WSJ can be easily detected from the I/B/E/S recommendation files which provide the last name and first initial of each analyst as well as their brokerage firm affiliation.

[24] All analysts, irrespective of their brokerage house affiliation are considered.

listed in Appendix II.[25] The heuristic employed in this ranking is purely based on quantitative analyses of returns on analyst recommendations. From a population of thousands of analysts, the top five performers in each industry are awarded the "Best on the Street" title each year.[26] The eligibility requirement for an analyst to be considered for the *WSJ* ranking is that they should have some sort of recommendation (buy/sell/hold) on at least 5 stocks in any one of the industry covered in the survey. Analyst ranking is based on "recommendation- performance scores" translated as the estimated total return, including price changes and dividends, of each eligible stock an analyst covered in an industry. Total scores are computed based on the recommendations of all the stocks in the analyst's portfolio. Return on a buy (sell) recommendation is multiplied by 1 (-1), strong buy (strong sell) is multiplied by 2 (-2) and a hold recommendation return is ignored (multiplied by zero).[27]

I identify superstars as *WSJ* stars with relatively higher success rate i.e. analysts who have appeared at least three times (if an analyst appeared in more than one category in a given year, I give him/her credit for both the appearances). The frequency heuristic so applied has its advantages in identification of a superstar. For example a rising star analyst who appears in three times in the last two years of the sample period of nine years is also identified as a superstar. However, in the analyses, I examine this very superstar's forecast characteristics in each year starting from 2002. The three year consideration deserves some discussion here. As discussed earlier, my purpose is to identify analysts that have been able to sustain their performance over time. To avoid making type II errors, it would be logical to select analysts who have been ranked

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[25] Every year the ranking is based on prior year's performance of analyst portfolio of recommendation. For eg. May 2002 publication reflects winning recommendations for the year 2001.

[26] "This year's Best on the Street analysts were selected from a universe of more than 6,800 analysts at more than 575 firms. Of that group, 2,335 analysts from 196 firms met the survey's eligibility tests and qualified to have their research analyzed in detail."- Wall Street Journal April 19, 2011

[27] Returns for each recommendation change (for example, an initial buy recommendation or a downgrade from buy to hold) were calculated beginning with the 4 p.m. (Eastern time) closing price the day before the change – WSJ Aug05, 2008.

for more than three years. However, sample size becomes an important consideration. Defining superstar analyst as the one who is ranked four instead of three times in the sample period, my sample size dramatically reduces to 46 analysts. By using a three year criterion, I am biasing against finding systematic forecast characteristics that are correlated to analysts' superior ability to process information.

Analysts' access to private information has significant influence on their forecast characteristics (Francis and Phillbrick 1993, Das et al. 1998). Regulation FD enforced restrictions on private disclosures so by restricting my data to post FD period, I minimize the influence of access to private information. The sample period is also post or the investment banking division (majority of the sample period is post NASD2711) of the brokerage firm.[28] The sample consists of analysts who have appeared in the rankings at least three times during the sample period of nine years.[29]

All the measures of earnings forecasts and recommendations used in this research come from Institutional-Brokers-Estimates-System (I/B/E/S) produced by Lynch, Jones, and Ryan. I/B/E/S History contains records on over 45,000 companies across 70 markets and is available from 1976 onwards. Stock analysts contribute their growth forecasts, earnings forecasts for the current and next fiscal year, and their recommendations to this database. I match the names of the superstar analysts identified from *WSJ* publication of "Best on the Street" with the I/B/E/S database and obtain their respective analyst codes. I use CRSP database to obtain daily returns on the stocks and COMPUSTAT for all firm related information.

For the test of ability, I examine superstar forecast characteristics in comparison with other analysts following the same firm. For that purpose, I identify firms followed by superstars

[28] RegFD came into effect on Oct 23, 2000 and NASD2711 came into effect on Dec 20, 2002.
[29] Analyst performance in a given year is evaluated and published in the next year. Hence the publication for the year 2003 includes analyst performance for the year 2002. So, my sample period is from 2002-2010.

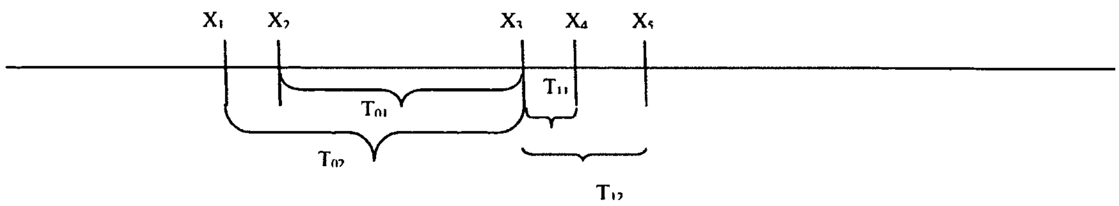
during the sample period of 2002-2010 and obtain all the available forecasts for these firm years. My final sample comprises of 239,528 (of which 34,824 belong to superstars) earnings forecasts covering 1260 firms and 5765 firm years.

To examine analyst characteristics, I include all the analysts with an annual earnings forecast from the I/B/E/S database for analyst forecasts. There are 4,628 unique analysts of which 88 are identified as superstars during my sample period.

# 7. Research Design

The purpose of this study is to identify analysts with superior stock picking skills and to assess their ability to process information. The first and second set of hypotheses relate to the examination of superstars' ability to process information. Literature has used two different benchmarks to evaluate analyst performance; the first one used by Stickel 1992 compares star analysts performance with all other analysts and the second one by Desai et al. 2000 who employ the "matching control company" method proposed by Barber and Lyon (1997). I employ the first approach and compare the characteristics of superstars' forecasts with those of other analysts (non-stars) following the same firms. This approach provides an automatic control for firm specific attributes such as its information environment etc. that could potentially influence analysts' forecast characteristics.

Since my objective is to analyze if there are any significant differences in the information processing ability of superstars compared to non-stars, I first employ univariate analyses to compare the means of these two groups of analysts. In other words, I use t-tests to examine if there are any significant differences in their ability to process information as indicated in their forecast revisions. As indicated in hypothesis H1A, I study analysts' efficiency in incorporating new information by examining how quickly they are able to revise their forecasts. To do so, I employ the timeliness measure from Cooper et al. (2001) and compute the Leader-follower ratio (LFR) for each analyst. LFR is defined as the ratio of the sum of number of days of two former forecasts and two following forecasts (pg 394 of Cooper et al. 2001). As depicted in the figure below, the LFR ratio for analyst $X_3$ can be computed as:




$$LFR = \frac{T_{01} + T_{02}}{T_{11} + T_{12}}$$

So, if the analyst is proficient in processing new information, his forecast revision will lead others as depicted in the figure above. Therefore, he will have a higher LFR value as the time lag between the prior forecast announcement and his forecast will be higher than the time lag between his forecast announcement and the following forecasts. Analysts have significant incentives in producing timely forecast revisions so that they can bring in more trading revenue which is why we see several forecast announcements on the same day (the phenomenon of clustering is commonly observed in analysts forecast revisions). I see a similar pattern in my data also. Hence, if two analysts announce forecasts on the same day, they both will have similar LFR scores; i.e. I give equal credit in terms of timeliness measure to each forecast announced on the same day.

For a forecast to provide information to the market participants it should not only be different from the consensus forecasts but should also be different from the analysts prior forecast. Stated differently, it should be both greater (lower) than the analyst's prior forecast as well as consensus forecast. So, I test hypothesis H1B by employing the method defined by Clement and Tse (2005). I identify an analyst's forecast as bold if the forecast is both greater (less) than his prior forecast as well as the consensus forecast calculated a day before the analysts forecast announcement. Based on this definition, I label all the forecast announcements as bold or not. In other words, if the analyst's forecast revision is greater (less) than his as well as consensus forecast, the boldness variable for that forecast takes the value 1 otherwise it takes the value zero.

To test the third hypothesis H1C, I compare the forecast error of superstars and non-stars. Forecast error is commonly defined as the absolute difference in the analysts' forecasts and the actual value of earnings scaled by the security price on prior day. I scale this measure by price on the prior day to make the resulting variable statistically comparable.

$$FORERR_{i,j,t} = \frac{|FORECAST_{i,j,t} - ACTUAL_{j,t}|}{PRICE_{j,t-1}}$$

Hypotheses 2 – Tests of Market Reaction

The second set of hypotheses examines the price and volume reaction around analysts' recommendation /forecast announcements. Efficient market theory posits that new information is immediately absorbed in the price of the security; therefore short term market reaction has been widely used to evaluate the significance of any new information to investors. I examine the cumulative abnormal returns (CAR) around analyst recommendation revisions. Recommendation revisions (RECCHNG) are computed as the difference in the analyst revised recommendation and the mean of the prior five recommendations.[30] Recommendation takes a value from 1 (strong buy) to 5 (strong sell) and the value 3 for any hold recommendations. So, if the consensus recommendation is 2.5 and the analyst revised recommendation is 2, then RECCHNG will be computed as 2.5-2 = 0.5 which indicates positive news as it is upgraded from 2.5 to 2.

Other controls – Prior studies have documented the effect of size (Bhushan 1989), analyst following (Imhoff and Lobo 1989) as well as dispersion in existing recommendations as a

[30] Recent announcements are more reflective of existing market sentiments (Singh et al. 1997) so I compute the information content in analyst recommendation by comparing it with the existing consensus in recent recommendations

measure of firm's information asymmetry. The level of information asymmetry defines the market reaction to new information. If there is a lot of uncertainty about the firm, the market reaction will be comparatively relatively higher for any new information about the firm. I use the logarithmic transformation of SIZE (defined as the market value of the firm two days prior to the recommendation revision) to mitigate econometric problems associated with skewness and heteroskedasticity. *CAR* and *CARV* represent the cumulative abnormal return (volume) around analysts' announcements of recommendations and earnings forecasts

I employ the following OLS regressions to examine the effect of superstar recommendation revisions on security price and the volume:

$$CAR_{it} = \alpha_0 + \alpha_1 STAR_{ijt} + \alpha_2 RECCHNG_{ijt} + \alpha_3 STAR * RECCHNG_{ijt} + \alpha_4 LNSIZE_{jt-2} + \alpha_5 RECFREQ_{ijt} + \alpha_6 RECDISP_{jt-2} + \alpha_7 STAR * RECDISP_{jt-2} + \varepsilon \qquad \ldots\ldots. (1)$$

$$CARV_{it} = \alpha_0 + \alpha_8 STAR_{ijt} + \alpha_9 ABSRECCHNG_{ijt} + \alpha_{10} STAR * ABSRECCHNG_{ijt} + \alpha_{11} LNSIZE_{jt-2} + \alpha_{12} RECFREQ_{ijt} + \alpha_{13} RECDISP_{jt-2} + \alpha_{14} STAR * RECDISP_{jt-2} + \varepsilon \qquad \ldots\ldots. (1b)$$

If superstars provide relatively more information in their recommendation revisions, the value of $\alpha_3$ will be positive and significant. The value of the coefficient of the control variables such as $\alpha_4$ is expected to be negative as the information environment of large firms is considerably better than small firms. In the same vein, the value of $\alpha_6$ is also expected to be negative.

Next, I employ a test of short term market reaction to examine the information content of forecast revisions as a test of hypothesis 2b. I use similar method employed in the evaluation of recommendation revisions except in these tests, the variable of interest will be forecast revision. I also include institutional holding as a control variable as majority of the market reaction is expected to come from institutional trades based on forecast revisions. Institutional investors employ their own heuristics to determine the investment value of new information. They are less likely to follow recommendations provided by sell-side analysts; albeit they are known to utilize analyst forecasts in their analyses. Therefore institutional holding is likely to affect the short term price and volume reaction to forecast revisions. I define BLKHOLDING as the percent of total outstanding shares held by institutional investors. FORDISP is defined as the standard deviation of the consensus forecast on the prior day. Forecast surprise (FORSURP) is computed as the difference in the analyst forecast and the existing consensus forecast scaled by the standard deviation of the existing forecasts as shown below:

$$FORSURP_{i,j,t} = \frac{FORECAST_{i,j,t} - CONSENSUS_{j,t-1}}{CONSENSUS_{j,t-1}}$$

*CAR* and *CARV* represent the cumulative abnormal return (volume) around analysts' announcements of annual earnings forecast revisions. I employ the following regression equations to evaluate the price (equation 2a) and volume (equation 2b) reactions to the incremental component (forecast surprise) of analyst forecast announcements.

$$\begin{aligned} CAR_{it} = {} & \beta_0 + \beta_1 STAR_{ijt} + \beta_2 FORSURP_{ijt} + \beta_3 STAR * FORSURP_{ijt} + \beta_4 LNSIZE_{jt-2} \\ & + \beta_5 FORDISP_{ijt-1} + \beta_6 STAR * FORDISP_{ijt-1} + \beta_7 ANALYSFOLL_{jt} \\ & + \beta_8 BLKHOLDING_{jt-2} + \varepsilon \end{aligned}$$

......∴ (2a)

$$CARV_{it} = \beta_0 + \beta_9 STAR_{ijt} + \beta_{10} ABSFORSURP_{ijt} + \beta_{11} STAR * ABSFORSURP_{ijt} + \beta_{12} LNSIZE_{jt-2} + \beta_{13} FORDISP_{ijt-1} + \beta_{14} STAR * FORDISP_{ijt-1} + \beta_{15} ANALYSFOLL_{jt} + \beta_{16} BLKHOLDING_{jt-2} + \varepsilon$$

....... (2b)

I examine the market reaction for one, two and three days after the announcement as three additional windows starting a day before the announcement and ending one, two and three days after the announcement to capture any reaction due to information provided privately before the announcement date in I/B/E/S. I apply similar controls as discussed in the earlier tests and commonly employed in the examination of abnormal market reaction to an information event. All the variables are described in Appendix I.

The variables of interest to test hypothesis 2b are $\beta_3$ and $\beta_{11}$. If the superstars indeed provide significantly more information in their forecasts, the market reaction is expected to be significant different for the two groups of analysts; superstars and all others.

Analyst Characteristics:

In order to examine if the role of analyst attributes such as experience, brokerage house affiliation and work load in their likelihood to be successful, I apply two unique methods. First I employ a univariate test of differences in means (t-test) to examine if the superstars exhibit any significant differences compared to an average analyst. Second, I use a logistic regression to examine the incremental effect of these attributes on the likelihood of analyst to become a superstar. In the first method, I test the difference in two ways: one by using analyst years and the second by comparing average value of analyst attributes. In the second method, I take the mean value of all the attributes so as to have only one observation per analyst. I employ the following logit regression where the dependent variable is an ordinal variable that takes the value one for superstars.

$$STAR = \gamma_0 + \gamma_1 EXP_{i,t} + \gamma_2 BRKSIZE_{i,t} + \gamma_3 PORTFOLIO_{i,t} + \gamma_4 FIRMFOLL_{i,t} \quad \ldots. (3)$$

The variable EXP measures the overall experience of the sell - side analyst in the profession. It is calculated as the total number of years of employment as an analyst. Analyst access to resources is measured as the size of the brokerage house which in turn is computed based on the number of analysts employed by it. Finally, the measure of work load and analyst expertise is calculated as the average number of firms followed by the analyst in a given year as well as over the sample period of nine years.

Based on prior findings and my conjecture, I expect a positive effect of experience and size of brokerage house affiliation on the likelihood of analysts' success; in other words, I expect $\gamma_1$ and $\gamma_2$ to be positive and significant. Alternatively, analysts work load and the complexity of their work is expected to have a negative effect on their ability to be successful; therefore I expect the coefficient of these two variables $\gamma_3$ and $\gamma_4$ to be negative and significant.

Superstar Stock picks:

In the final set of analyses, I examine the attributes of superstar stock picks. Specifically I employ univariate analyses of the difference in the means of the stock picks by superstars and other analysts. I also employ a logistic regression to examine the incremental effect of each of these attributes in superstars' likelihood to pick the firm. I use the following equation to test the effect of these attributes:

$$STAR = \chi_1 + \chi_2 ANALYSFOLL_{it} + \chi_2 BTM_{it} + \chi_4 LNSIZE_{it} + \chi_5 BETA_{it} + \chi_6 BLKHLD_{it} + \chi_7 LNASSETS_{it} + \varepsilon$$

$$\ldots\ldots\ldots\ldots\ldots (4)$$

The firm attributes that I study are market to book value (calculated as the ratio of the book value per share to the current price), market capitalization (computed as the product of shares outstanding and the current price), firm size (computed as the log of assets on the prior year's annual report) and the percentage of block holding (computed as the ratio of shared held by institutional investors to the total shares outstanding). Also, I define analyst following as the number of analysts following the stock in a given year. A detailed description of these variables is also provided in Appendix III.

# 8. Results

Descriptive Statistics:

Appendix 1 (Panel A) illustrates the frequency distribution of stars from WSJ's annual publication from 2003-2011. Whereas the total number of unique analysts who won the "Best on the Street" award is 1092, only 93 analysts demonstrated relative consistency in their ability to identify winning securities.[31] Superstars were identified based on the frequency of ranking. Industry distribution of superstars depicts that the probability of success in picking stocks appears to be higher in certain industries. In particular, analysts seem to be more likely to succeed in their ability to predict future returns in consumer based industries such as retail, hotels and casinos, wireless telecommunication. Interestingly, I also find a higher frequency of analyst success as superstars in aerospace and defense. I have a list of all the superstar analysts so I examined the five analysts that have exhibited superior ability in the aerospace industry. Three of the five superstars belong to smaller brokerage firms which could indicate that these analysts are not only experts in this industry but also that their choice to follow this industry may be motivated by client preference more than brokerage revenue. I also, examine the number of firms followed by superstars in each of the twelve industries and find that the highest concentration (47%) is in the consumer-nondurables industry which includes retail industry followed by transportation which contains 38% star stock picks (Appendix I, Panel C).

Test of ability

Descriptive statistics show that about 68 percent of analysts' forecasts are bold suggesting that on average analysts provide significant incremental information in their forecasts. This

[31] One exception is the evidence from Emery and Li (2009). They find that performance measures are significant determinants of whether an analyst becomes a star or not. However, for *WSJ* stars, they find that the performance deteriorates in the subsequent year after becoming a star. If that is the case, it would work against my hypotheses of ability during and in years when the stars are not ranked.

provides substantive evidence that analysts play a significant role as information providers in the capital market. Test of difference in means suggests that superstars are leaders in forecast announcements. In particular difference in the average leader-follower ratio (LFR), a measure of timeliness in forecast is significantly high (the superstars have a ratio of 2.36 compared to other analysts ratio of 2.14). This suggests that superstars respond relatively faster to new information. Also the second measure depicting analyst leadership in forecasts, boldness, is also significantly higher for superstars (71% forecasts are bold) compared to other analysts (68% have bold forecasts). However, I do not find any significant difference in the forecast accuracy of superstars and other analysts.[32] This demonstrates the tradeoffs between accuracy and timelines of forecast announcements. Analysts with timely forecasts attract higher trading volume resulting in higher brokerage revenue for the firms. Therefore, it must be the case that these analysts put more emphasis on providing timely forecasts. Absolute forecast surprise captures the information content of the forecast. T-test results (Table 1, Panel B) indicate that on average, the information content of superstar forecast announcements (0.973) is significantly higher than other analysts (0.917). Univariate results suggest that superstars comparatively provide timely and significantly more information in their forecast announcements.

CAR Analyses

Market reaction to forecast and recommendation revisions has been used as a measure of the information content in analyst announcements. A significant market reaction (price and/or volume) indicates that investors attach substantial value to the new information provided in analyst forecast/recommendation revisions. My results (discussed in detail below) demonstrate the superiority of superstars' ability to process information.

[32] In untabulated results, I also examine the difference in forecast accuracy of superstars and non-stars by taking the latest forecast for each analyst firm year. The multivariate tests results indicate that forecast error is not significantly different.

Forecast Revisions:

Price and volume reactions to analyst forecasts provide incremental evidence on the superiority of the processing ability of superstars. Examination of the cumulative abnormal return on the forecast announcements indicates a significant association with the information content in analyst forecast (as indicated by the value of $\beta_3$= .006). The coefficient of the interaction of star and forecast surprise ($\beta_4$= .004) measures the incremental reaction to the information content of superstar forecast. Thus, the total abnormal return to the superstar forecasts is 1% over a short period of one, two and three days after the announcement.[33] Other variables also behave in concurrence with prior literature. In particular, the excess returns are more for firms with higher heterogeneity in beliefs (higher forecast dispersion) as depicted by the value of coefficient ($\beta_4$ =0.008). In fact, the economic significance of this relation quadruples ($\beta_3$= 0.032) for superstar forecasts. Examination of change in trading volume surrounding forecast announcements signifies the impact of absolute forecast surprises on market sentiments. The results illustrate a significant abnormal trading associated with average absolute forecast surprises ($\beta_9$= 0.156) and this association is even stronger for superstar forecasts ($\beta_{10}$= 0.061). This suggests that the superstar forecast announcements on average contribute to 21.7% increase in trading (0.156 + 0.061). Although heterogeneity in beliefs of market participants draw significantly higher market reaction (abnormal returns), the volume analyses indicate a muted market response to absolute forecast surprises. This could be interpreted as the reluctance of investors to trade in a security with high dispersion in beliefs. Other variables such as firm-size,

[33] Please note that this test included all the forecasts. If I exclude the forecasts from other analysts on the same day as the superstar forecasts, the untabulated results are significantly higher.

block-holding and analyst following concur with prior findings in that they are significant and in the right direction.

Recommendation Changes:

Table 2 illustrates the results of market analyses of recommendation revisions (test of hypotheses 2). The results indicate significant abnormal returns around recommendation revisions ($\alpha_2 = 0.016$) and this reaction is 1.5 times stronger for superstar revisions ($\alpha_2+\alpha_3= 0.023$). The abnormal trading volume associated with the absolute change in forecast is also economically and statistically significant ($\alpha_9 = 0.25$). However, there is no differential reaction for superstar recommendation revisions. One of the reasons why this could be the case is that institutional investors, the ones that utilize analyst information do not make investment decision on recommendations compared to the decisions related to analyst forecasts. The volume that appears could be related to individual investors who may not follow or even have timely access to superstar recommendations.

Analyst Characteristics:

An analysis of characteristics of superstars is illustrated in Table 4. The descriptive statistics (Table 4, Panel A) indicate that an average analyst on the Wall Street has about eight to nine years of experience. Of the total sample size of 2,861 analysts identified in the I/B/E/S database, 1,430 have over seven years of overall experience as an analyst.

On average analysts follow a little over one industry in any given year. The maximum number of industries (firms) followed by any analyst is about four (nine). Test of difference in average characteristics of superstars compared to an average Wall Street analyst indicates that the superstars have twice the experience. This substantiates the findings of prior literature that experience is one of the leading indicators of ability (Clement 1999, Jacob et al. 1999). However, contrary to their findings, I document that superstars hail from relatively smaller brokerage firms. In a way this result is not surprising considering the recent increase in analyst regulations. Employment at larger brokerage house may come with lot of restrictions and may also inhibit the development of an analyst with ability. Indeed, anecdotal evidence suggests that some of the larger brokerage houses have lost talented employees in the wake of recent regulations.[34] The results of significant impact of experience and size of brokerage house hold in the multivariate analyses which suggest a higher likelihood of analyst with experience and affiliation with smaller brokerage houses to become superstars. However, the results don't hold for the portfolio complexity or number of firms followed by the analyst signifying that work load may not affect the likelihood to become superstar.

Firm Characteristics:

An analysis of superstar stock picks is provided in Table 5. Average stock pick of a superstar analyst is significantly larger than an average Wall Street analyst. Analyses of difference in means indicate that superstars follow value stock (the average book-to-market value of superstar stock is 0.55). The average market capitalization (asset value) of superstar stock is 14.65 (7.99) compared to 13.65 (7.11) for another analyst. Also, investment banking holding is higher (0.77) for superstar stock picks compared to an average analyst (0.66). These differences are economically and statistically significant. Multivariate analyses on the likelihood of a superstar stock picks supports the univariate results and indicated that superstars prefer to pick larger, value stocks with high investment banking holding. This provides further evidence on the significance of large investors in analyst's decision to pick a stock.

[34] "Stock Research Reforms to Die" - Kim, The Wall Street Journal, June 9, 2009 – available at http://online.wsj.com/article/SB124450523620696089.html#mod=WSJ_topics_obama

Superstar Stock picks:

Results on attributes of firms followed by superstars are provided in Table 5. The first table provides a correlation between the major firm characteristics. All these attributes are highly correlated. Difference in the means of characteristics of firms followed by superstars compared to other analysts indicates the former's penchant to follow larger firms (both the size variables, LNSIZE (=14.65) and LNASSETS (=7.98) are significantly higher for superstar firms compared to other analysts. However, the market value result reverses in the multivariate analysis (coefficient of LNSIZE $\chi_3 = -0.19$ is statistically significant). This indicates that given other attributes, superstars are likely to follow growth firms with comparatively lower market value.

Results of t-tests on other attributes represented in Table 6 Panel B suggests that superstar firms have significantly higher analyst following – average 9.2 analyst follow these firms compared to 5.5 for other firms. Additionally, the firms followed by superstars have significantly higher institutional investment which is indicative of their preference to invest in research that is beneficial to their largest clients. Results indicate that superstars tend to follow glamour firms i.e. firms with low book to market ratio (the difference in means is .048 and is significant at 1%). Finally, multivariate logistic test results reveal that a superstar is significantly less likely to pick a value firm but is more likely to follow firms with higher institutional holding.

This indicates that brokerage commissions play a significant role in superstars' decision to follow a stock, especially in the period post NASD2711. Prior to this regulation, analysts bonuses were also influenced by the investment banking division but in the post NASD2711 period, the Chinese wall between the research and investment banking department prohibits such mingling of finance. Hence, the analysts' research during this period is entirely funded by their ability to procure brokerage business.

# 9. Robustness Tests

Comparison of the performance of superstars with other analysts provides a significant evidence of their superiority in processing information. However, it does not provide any indication on whether an investor would be better off by following the recommendations of these analysts. In other words, considering market efficiencies, are these analyst able to consistently beat the market. To test this, I prepare annual portfolios for all the nine years from 2002- 2010 for each of the 82 superstars. The idea is to evaluate the performance of their portfolio (based on their recommendations) compared to the performance of market (S&P 500).

The methodology employed in preparing these portfolios is similar to the *WSJ* methodology. I calculate the return on analyst recommendations: return on a (strong) buy recommendation is multiplied by 2 (1) whereas a return on (strong) sell recommendation is multiplied by -2 (-1) and hold recommendations are multiplied by zero (the analyst gets no credit for a hold recommendation).

Prior literature has suggested that increased analyst regulations, particularly post RegFD and NASD2711 have led to a decrease in analyst optimism (Barber et. al, 2006, Kadan et al. 2009). In particular, Barber et al. (2006) document that the distribution of recommendations has become more balanced i.e. number of sell recommendations has increased compared to the pre-RegFD period. Kadan et al. (2009) find that analyst recommendations have become less informative as majority recommendations are based on three tier system instead of a five tier system that was prevalent in the pre regulation period. I examine the distribution of superstar recommendations in during the sample period (see table 6A). The results contradict prior findings; sell recommendations, on average, comprise of only 10% of the total number of recommendations announced by superstars.[35] There could be a couple of reasons that might explain this pattern: it first, it could be the case that the superstars continue to nourish their relationship with the management or it could be the case that sell recommendations are not as valuable to investors due to their unwillingness to take a short position. Hence, the analyst may prefer to drop the coverage on a firm instead of assigning it as a sell.

Analyses of portfolio returns indicate that on average the superstars perform well (see table 6B). Annual mean and median returns of the superstars' portfolio suggest that the average unadjusted return on superstar portfolio is positive in each year of the sample period (2002 to 2010). However, the market adjusted returns are not positive in the years 2003 and 2006. Interestingly, in the years 2002 and 2008 when the market crashed and S&P 500 dropped a whopping 21% (246 points) 38% (565 points), an average superstar excelled with an unadjusted return of 43% and 18% (adjusted return of 142% and 124% ) respectively.

A detailed examination of the portfolio returns on each of the 82 superstars reveals that not all of them exhibit consistency in performance over a span of 9 years. In particular, my findings suggest that of these 82 superstars, portfolios of 22 superstars displayed negative cumulative abnormal returns over a period of 9 years of which only 12 superstars' portfolios earned absolute negative total returns. However, the overall return on the superstars' portfolios was significantly positive. The abnormal return over a period of nine years was 417.71 percent whereas the absolute return was 595.42 percent. This result has several implications: first, 60 superstars are significantly superior in their ability to consistently beat the market. Collectively, the total return on their recommendation portfolio is 595.08 percent whereas the abnormal return is 511.17

[35] However, note the hold recommendations are about 40% of the total recommendations so if that is interpreted as a negative signal, then the positive and negative signals in terms of recommendations are comparable.

percent. This finding is of great value to the market participants who face a wide choice of analysts' recommendations to follow.

# 10. Conclusions and Future Research

In this study, I examine the characteristics of superstars defined as analysts with the ability to consistently provide winning recommendations. Analyst recommendations could be a result of their superior ability to process information or their penchant for high momentum/ high growth stocks (Jegadeesh et al. 2004). So, to examine the role of analysts' ability to process information in their recommendations, I conduct an in-depth analysis of a sample of analysts from the *WSJ* rankings.

I hypothesize and document systematic differences in the superstars' ability to incorporate new information in their forecast revisions compared to other analysts. I also document that superstars' forecasts provide significant more investment value to the market participants. My findings corroborate with the existing literature on analyst characteristics. The results indicate that the superstars consistently provide value relevant information in their forecasts in that they are efficient in incorporating new information in their forecast revisions. In particular, their forecasts are timelier as well as bold, characteristics attributed to a leader analyst (Cooper et al. 2000, Gleason and Lee 2003, Clement and Tse 2005). Additionally, the results for price and volume reaction on forecast and recommendation revisions also indicate the significance of their outputs; in other words, the market recognizes these analysts as superstars and ascribes significant value to their forecast/recommendation revisions.

I also examine the characteristics of superstars and document that these analysts have significant experience which appears to be the most significant attribute of their ability. Contrary to the findings of prior research, my results do not support the role of brokerage house affiliation or portfolio complexity in these analysts likelihood to succeed as superstars.

Finally, an examination of superstar stock picks suggests provides some insight into their preference. The results indicate that the superstars prefer to follow value stocks with high institutional holding. Also, the stocks followed by superstars have significantly higher analyst following. This suggests the significance of brokerage revenue to analysts.

Future Research:

*WSJ* annually prepares portfolios based on the recommendations of a population of analysts. Based on my analyses in this study, it is apparent that analysts have significant incentives to pick risky stocks in order to improve their chances to win in the *WSJ* rankings; which in turn explains the high turnover of the rankings. In the current methodology applied by the WSJ, analysts get a fresh shot each year; on other words, they are not penalized for bad performance in prior years. Hence, it would be interesting to analyze the performance of the one-time stars in the year prior to their wining the WSJ contest as well as in the post year. Additionally, an analysis of their stock picks would also confirm/reject the conjecture of the role of luck in their winning.

Secondly, I recommend a modification in the existing heuristic employed by *WSJ* in their annual analyst rankings. The current methodology employed by the WSJ is represents a myopic analyses of analyst ability. Thus, analyst performance in prior years is ignored for the purpose of the current year rankings which make this "tournament" type process to lean towards an outcome of luck instead of analysts' consistent ability to process information. So, one way to enhance the probability of *WSJ* rankings to identify analysts with superior skills is to include prior performance in its algorithm of assigning star rankings. This will serve two purposes – first, it will provide relative assurance of the star analyst's future performance to the users of the ranking and second it will weed out most of the onetime analysts who thrive on a lucky stock pick. For future research, I propose to provide analyst rankings based on a three year cumulative returns on their portfolios.

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# 12. Appendices

**Appendix I (Panel A) *WSJ* Star Frequency of winning**

| Description | Number of Analysts |
|---|---|
| One Time Stars | 810 |
| Two Time Stars | 189 |
| Three Time Stars | 70 |
| Four Time Stars | 13 |
| Five Time Stars | 8 |
| Six Time Stars | 2 |
| TOTAL STARS | 1092 |

**Appendix I (Panel B) Industry Distribution of Superstars**

| Industry | Superstar Count | Industry | Superstar Count |
|---|---|---|---|
| Retailers | 6 | General Industrials | 2 |
| Aerospace & Defense | 5 | Heavy Machinery & Materials | 2 |
| Hotels & Casinos | 5 | Internet & Computer Services | 2 |
| Household & Personal Products | 5 | Mining & Metals | 2 |
| Insurance | 4 | Oil & Gas | 2 |
| Telecommunications – Wireless | 4 | Utilities | 2 |
| Beverages | 3 | Advance Industrial Equip | 1 |
| Broadcasting & Entertainment | 3 | Advertising & Publishing | 1 |
| Chemicals | 3 | Banks | 1 |
| Electronic & Electrical Equipment | 3 | Health-Care Providers | 1 |
| Industrial Transportation | 3 | Medical Equipment & Supplies | 1 |
| Leisure Goods & Services | 3 | Pharmaceuticals | 1 |
| Airlines | 2 | Real Estate | 1 |
| Autos & Auto Parts | 2 | Restaurants | 1 |
| Biotechnology | 2 | Securities Brokers | 1 |
| Clothing & Accessories | 2 | Semiconductor-Equipment Manufacturing | 1 |
| Computers & Office Equipment | 2 | Software | 1 |
| Consumer & Specialty Finance | 2 | Telecommunications | 1 |
| Diversified Industrial | 2 | Telecommunications | 1 |
| Food & Tobacco | 2 | Thrift | 1 |

**Appendix I (Panel C) Analyst following by Industry**

| | | | Followed by Star | |
|---|---|---|---|---|
| IND | Description | Total firms | Number | Percent |
| 1 | FINANCE | 1024 | 162 | 15.8% |
| 2 | HEALTH | 737 | 142 | 19.3% |
| 3 | CONSUMER NON-DURABLES | 233 | 109 | 46.8% |
| 4 | CONSUMER SERVICES | 777 | 249 | 32.0% |
| 5 | CONSUMER DURABLES | 149 | 40 | 26.8% |
| 6 | ENERGY | 324 | 63 | 19.4% |
| 7 | TRANSPORTATION | 138 | 52 | 37.7% |
| 8 | TECHNOLOGY | 943 | 189 | 20.0% |
| 9 | BASIC INDUSTRY | 268 | 88 | 32.8% |
| 10 | CAPITAL GOODS | 331 | 117 | 35.3% |
| 11 | PUBLIC UTILITIES | 214 | 49 | 22.9% |

**<u>Appendix III – Definition of Variables</u>**

<u>FORECAST CHARACTERISTICS</u>

| | |
|---|---|
| BOLD | An indicator variable equal to 1 if the current forecast is greater (less) than the analyst's previous forecast as well as consensus forecast, 0 otherwise.(Ref. Clement and Tse, 2005) |
| LFR | Lead Follower Ratio calculated as (Sum of number of days of two prior forecasts)/ (Sum of number of days of two subsequent forecasts). Higher ratio indicates that the analyst is a leader – (Ref. Cooper et al. 2002) |
| FORERR | Absolute Forecast Error scaled by prior day's stock price |
| FORSURP | (Analyst Forecast Value - Lag Consensus Forecast)/Share Price at t-2 |
| ABSFORSURP | Absolute value of FORSURP |

<u>CAR ANALYSES -RECOMMENDATION</u>

| | |
|---|---|
| CAR | Cumulative Abnormal Return around recommendation announcements |
| CARV | Cumulative Abnormal Volume around recommendation announcements |
| STAR | Indicator variable = 1 if the analyst is a superstar, 0 otherwise |
| RECCHNG | Consensus Recommendation - Analyst Recommendation |
| SIZE | Market capitalization of the firm calculated as Share Price * Shares outstanding |
| LNSIZE | LOG (SIZE) |
| RECFREQ | Number of Recommendations for the firm |

<u>CAR ANALYSES - FORECAST SURPRISE</u>

| | |
|---|---|
| CAR | Cumulative Abnormal Return around forecast announcement |
| CARV | Cumulative Abnormal Volume around forecast announcement |
| FORSURP | (Analyst Forecast Value - Consensus Forecast)/ Share Price |
| STAR | Indicator variable = 1 if the analyst is a superstar, 0 otherwise |
| SIZE | Market capitalization of the firm calculated as Share Price * Shares outstanding |
| LNSIZE | LOG (SIZE) |
| FORDISP | Standard Deviation of consensus forecast scaled by share price |
| ANALYSFOLL | Number of analysts following the firm |
| BLKHOLDING | Percentage of total outstanding shares held by institutional investors in the quarter of analyst forecast announcement |

<u>ANALYST CHARACTERISTICS</u>

| | |
|---|---|
| EXP | Number of years of overall experience as an analyst |
| LNBRKSIZE | Log of the number of analysts employed by the brokerage firm in year t |
| PORTFOLIO | Number of industries followed by the analyst in year t |
| TOTFIRMS | Total number of firms followed by the analyst in year t |

FIRM CHARACTERISTICS

| | |
|---|---|
| ANALFOLLOW | Total number of analysts following the firm in year t |
| BTM | Book to Market Ratio (Book value per share/ Mkt Value per share) |
| SIZE | Market capitalization of the firm calculated as Share Price * Shares outstanding |
| LNSIZE | LOG (SIZE) |
| BETA | Measure of stock price senstitivity - Obtained from I/B/E/S |
| BLKHOLDING | Percentage of total outstanding shares held by institutional investors in the quarter of analyst forecast announcement |
| LNASSETS | Log of total Assets as of year t-1 |

# 13. Tables

**Table 1 – Test of Hypotheses 1A, 1B, 1C – Forecast Characteristics**

Panel A – Descriptive Statistics of Forecast Characteristics (Superstars and Non-Stars)

| VARIABLE | # OBS | MEAN | MIN | MED | MAX | STD DEV |
|---|---|---|---|---|---|---|
| BOLD | 239,529 | 0.685 | 0.000 | 1.000 | 1.000 | 0.465 |
| LFR | 229,987 | 2.171 | 0.003 | 1.000 | 29.833 | 3.512 |
| FORERR | 239,527 | 0.011 | -0.103 | 0.004 | 0.188 | 0.020 |
| FORSURP | 239,529 | 0.007 | -3.540 | 0.049 | 3.217 | 1.131 |
| ABSFORSURP | 239,529 | 0.925 | 0.000 | 0.828 | 3.540 | 0.651 |

Panel B – Descriptive Statistics of Forecast Characteristics (Superstars)

| VARIABLE | # OBS | MEAN | MIN | MED | MAX | STD DEV |
|---|---|---|---|---|---|---|
| BOLD | 34,824 | 0.708 | 0 | 1 | 1 | 0.455 |
| LFR | 32,929 | 2.356 | 0.004 | 1 | 29.83 | 3.877 |
| FORERR | 34,823 | 0.011 | -0.005 | 0.004 | 0.188 | 0.020 |
| FORSURP | 34,824 | -0.018 | -3.536 | 0.007 | 3.214 | 1.188 |
| ABSFORSURP | 34,824 | 0.973 | 0 | 0.874 | 3.536 | 0.681 |

Panel C – Test of difference in means

| | STARS (N=34,824) | NON-STARS (N=204,704) | | |
|---|---|---|---|---|
| VARIABLE | MEAN | MEAN | DIFF IN MEAN | T-STAT |
| BOLD | 0.708 | 0.681 | **0.027***** | 9.83 |
| LFR | 2.356 | 2.14 | **0.216***** | 10.31 |
| FORERR | 0.0106 | 0.0105 | 0.000 | 0.47 |
| FORSURP | -0.0179 | 0.0109 | **-0.0289***** | 4.39 |
| ABSFORSURP | 0.9734 | 0.9169 | **0.0565***** | 14.98 |

Panel D – Likelihood Test

| VARIABLE | Coefficient | P-Value | Odds Ratio |
|---|---|---|---|
| INTERCEPT | -1.9841 | <.0001 | |
| BOLD | **0.085** | <.0001 | 1.089 |
| LFR | 0.015 | <.0001 | 1.015 |
| FORERR | **-0.079** | <.0001 | 0.924 |
| ABSFORSURP | **0.108** | <.0001 | 1.114 |

$R^2 = 0.03$

32,929 Superstar and 197,058 non-star observations

## Table 2 – Test of Hypotheses 2A – Market Reaction to Recommendation Changes

Panel A – Difference in means – Cumulative Abnormal Return/Volume

| Market Reaction | SUPERSTARS (N=6,727) MEAN | NON-STARS (N=189,638) MEAN | DIFF IN MEAN | T-STAT |
|---|---|---|---|---|
| CARV 1 (0,+1) | 0.8559 | 0.626 | **0.2299** | 11.66 |
| CARV 2 (0,+2) | 1.048 | 0.7696 | **0.2784** | 10.22 |
| CARV 3 (0,+3) | 1.185 | 0.876 | **0.309** | 9.00 |
| CARV 4 (-1,+1) | 1.069 | 0.8038 | **0.2652** | 9.70 |
| CARV 5 (-1,+2) | 1.261 | 0.9474 | **0.3136** | 9.05 |
| CARV 6 (-1,+3) | 1.398 | 1.0538 | **0.3442** | 8.27 |
| CAR 1 (0,+1) | -0.002 | -0.002 | 0.00 | 0.25 |
| CAR 2 (0,+2) | -0.003 | -0.002 | 0.00 | 0.64 |
| CAR 3 (0,+3) | -0.003 | -0.003 | 0.00 | 0.01 |
| CAR 4 (-1,0) | -0.003 | -0.003 | 0.00 | 0.10 |
| CAR 5 (-1,+1) | -0.003 | -0.003 | 0.00 | 0.28 |
| CAR 6 (-1,+2) | -0.004 | -0.004 | 0.00 | 0.10 |

Panel B – Cumulative Abnormal Return

$$CAR_{it} = \alpha_0 + \alpha_1 STAR_{ijt} + \alpha_2 RECCHNG_{ijt} + \alpha_3 STAR * RECCHNG_{ijt} + \alpha_4 LNSIZE_{jt-2} + \alpha_5 RECFREQ_{ijt} + \alpha_6 RECDISP_{jt-2} + \alpha_7 STAR * RECDISP_{jt-2} + \varepsilon$$

| Variables | CAR 1 (0,+1) | | CAR 2 (0,+2) | | CAR 3 (0,+3) | |
|---|---|---|---|---|---|---|
| | Coeff. | P-Value | Coeff. | P-Value | Coeff. | P-Value |
| Intercept | 0.006 | <.0001 | 0.007 | <.0001 | 0.010 | <.0001 |
| STAR | -0.003 | 0.438 | -0.003 | 0.435 | 0.001 | 0.910 |
| CHNG | **0.016** | <.0001 | **0.017** | <.0001 | **0.017** | <.0001 |
| CHNG * STAR | **0.007** | <.0001 | **0.007** | <.0001 | **0.007** | <.0001 |
| LNSIZE | -0.001 | <.0001 | -0.001 | <.0001 | -0.001 | <.0001 |
| RECDISP | **0.002** | 0.005 | **0.003** | <.0001 | **0.004** | <.0001 |
| RECDISP * STAR | 0.002 | 0.583 | 0.002 | 0.638 | -0.002 | 0.768 |
| RECFREQ | 0.000 | <.0001 | 0.000 | <.0001 | 0.000 | <.0001 |
| Adj $R^2$ | | .05 | | .048 | | .045 |

There were 6,727 star observations and 189,638 non-star observations

Panel C – Cumulative Abnormal Volume

$$CARV_{it} = \alpha_0 + \alpha_8 STAR_{ijt} + \alpha_9 ABSRECCHNG_{ijt} + \alpha_{10} STAR * ABSRECCHNG_{ijt} + \alpha_{11} LNSIZE_{jt-2} + \alpha_{12} RECFREQ_{ijt} + \alpha_{13} RECDISP_{jt-2} + \alpha_{14} STAR * RECDISP_{jt-2} + \varepsilon$$

| Variables | CARV 1 (0,+1) | | CARV 2 (0,+2) | | CARV 3 (0,+3) | |
|---|---|---|---|---|---|---|
| | Coeff. | P-Value | Coeff. | P-Value | Coeff. | P-Value |
| Intercept | 2.266 | <.0001 | 1.867 | <.0001 | 2.509 | <.0001 |
| STAR | 0.133 | 0.294 | 0.100 | 0.278 | 0.175 | 0.277 |
| ABSCHNG | **0.187** | <.0001 | **0.144** | <.0001 | **0.221** | <.0001 |
| ABSCHNG * STAR | -0.002 | 0.969 | 0.012 | 0.726 | -0.017 | 0.775 |
| LNSIZE | -0.111 | <.0001 | -0.094 | <.0001 | -0.119 | <.0001 |
| RECDISP | 0.021 | 0.330 | **0.045** | 0.004 | 0.001 | 0.976 |
| RECDISP * STAR | 0.198 | 0.154 | 0.161 | 0.108 | 0.202 | 0.248 |
| RECFREQ | -0.002 | <.0001 | -0.001 | <.0001 | -0.003 | <.0001 |
| Adj $R^2$ | | .020 | | .016 | | .014 |

**Table 3 – Test of Hypotheses 2B – Market Reaction to Forecast Surprises**

Panel A – Difference in means – Cumulative Abnormal Return/Volume

| | SUPERSTARS (N=34,795) | NON-STARS (N=204,569) | | |
|---|---|---|---|---|
| Market Reaction | MEAN | MEAN | DIFF IN MEAN | T-STAT |
| CARV 1 (0,+1) | 0.6433 | 0.4024 | **0.2409** | 38.76 |
| CARV 2 (0,+2) | 0.758 | 0.4714 | **0.2866** | 33.87 |
| CARV 3 (0,+3) | 0.821 | 0.506 | **0.315** | 29.81 |
| CARV 4 (-1,+1) | 0.8989 | 0.5724 | **0.3265** | 37.73 |
| CARV 5 (-1,+2) | 1.014 | 0.6414 | **0.3726** | 34.44 |
| CARV 6 (-1,+3) | 1.077 | 0.6756 | **0.4014** | 31.19 |
| CAR 1 (0,+1) | -0.0008 | -0.0002 | -0.0006 | -1.8 |
| CAR 2 (0,+2) | -0.0012 | -0.0004 | -0.0008 | -2.51 |
| CAR 3 (0,+3) | -0.0012 | -0.0005 | -0.0007 | -1.71 |
| CAR 4 (-1,+1) | -0.0008 | -0.0004 | -0.0004 | 1.06 |
| CAR 5 (-1,+2) | -0.0012 | -0.0005 | -0.0007 | -1.73 |
| CAR 6 (-1,+3) | -0.0011 | -0.0006 | -0.0005 | 1.11 |

Panel B – Cumulative Abnormal Return

$$CAR_{it} = \beta_0 + \beta_1 STAR_{ijt} + \beta_2 FORSURP_{ijt} + \beta_3 STAR * FORSURP_{ijt} + \beta_4 LNSIZE_{jt-2} + \beta_5 FORDISP_{ijt-1}$$
$$+ \beta_6 STAR * FORDISP_{ijt-1} + \beta_7 ANALYSFOLL_{jt} + \beta_8 BLKHOLDING_{jt-2} + \varepsilon$$

| Variables | CAR 1 (0,+1) | | CAR 2 (0,+2) | | CAR 3 (0,+3) | |
|---|---|---|---|---|---|---|
| | Coeff. | P-Value | Coeff. | P-Value | Coeff. | P-Value |
| Intercept | 0.009 | <.0001 | 0.009 | <.0001 | 0.009 | <.0001 |
| FORSURP | **0.006** | <.0001 | **0.006** | <.0001 | **0.006** | <.0001 |
| FORSURP * STAR | **0.004** | <.0001 | **0.004** | <.0001 | **0.004** | <.0001 |
| STAR | -0.001 | 0.001 | **-0.001** | 0.002 | **-0.001** | 0.015 |
| LNSIZE | -0.001 | <.0001 | -0.001 | <.0001 | -0.001 | <.0001 |
| FORDISP | 0.008 | 0.190 | 0.013 | 0.047 | 0.020 | 0.006 |
| FORDISP*STAR | **0.032** | 0.006 | 0.015 | 0.245 | 0.010 | 0.479 |
| ANALYSFOLL | 0.000 | 0.000 | 0.000 | 0.005 | 0.000 | 0.001 |
| BLKHOLDING | 0.001 | 0.020 | 0.002 | 0.009 | 0.002 | 0.000 |
| Adjusted $R^2$ | | .023 | | .019 | | .016 |

Coefficients of interest appear in bold

Panel C – Cumulative Abnormal Volume

$$CARV_{it} = \beta_0 + \beta_9 STAR_{ijt} + \beta_{10} ABSFORSURP_{ijt} + \beta_{11} STAR * ABSFORSURP_{ijt} + \beta_{12} LNSIZE_{jt-2} + \beta_{13} FORDISP_{ijt-1}$$
$$+ \beta_{14} STAR * FORDISP_{ijt-1} + \beta_{15} ANALYSFOLL_{jt} + \beta_{16} BLKHOLDING_{jt-2} + \varepsilon$$

| Variables | CARV 1 (0,+1) | | CARV 2 (0,+2) | | CARV 3 (0,+3) | |
|---|---|---|---|---|---|---|
| | Coeff. | P-Value | Coeff. | P-Value | Coeff. | P-Value |
| Intercept | 1.238 | <.0001 | 1.401 | <.0001 | 1.423 | <.0001 |
| ABSFORSURP | **0.156** | <.0001 | **0.210** | <.0001 | **0.255** | <.0001 |
| ABSFORSURP*STAR | **0.061** | <.0001 | **0.074** | <.0001 | **0.088** | <.0001 |
| STAR | 0.122 | <.0001 | **0.138** | <.0001 | **0.141** | <.0001 |
| LNSIZE | -0.067 | <.0001 | -0.076 | <.0001 | -0.079 | <.0001 |
| FORDISP | -1.681 | <.0001 | -1.554 | <.0001 | -1.259 | <.0001 |
| FORDISP*STAR | **-0.556** | 0.028 | **-0.952** | 0.006 | **-1.338** | 0.002 |
| ANALYSFOLL | **-0.004** | <.0001 | **-0.006** | <.0001 | **-0.008** | <.0001 |
| BLKHOLDING | **0.216** | <.0001 | **0.275** | <.0001 | **0.330** | <.0001 |
| Adjusted $R^2$ | | .037 | | .032 | | .027 |

Coefficients of interest appear in bold

## Table 4 – Test of Hypotheses 3A, 3B, 3C – Analyst Characteristics

Panel A – Descriptive Statistics

| VARIABLE | # OBS | MIN | MED | MAX | MEAN | STD DEV |
|---|---|---|---|---|---|---|
| EXP | 2,861 | 1.00 | 7 | 30 | 8.680 | 5.955 |
| LNBRKSIZE | 2,861 | 0.76 | 4.05 | 5.10 | 4.069 | 0.807 |
| PORTFOLIO | 2,861 | 1.00 | 1 | 4.5 | 1.254 | 0.455 |
| TOTFIRMS | 2,861 | 2.00 | 8.57 | 62 | 8.813 | 4.736 |

Panel B – Test of Difference in means

| | STARS (N=88) | NON-STARS (N=2,773) | | |
|---|---|---|---|---|
| VARIABLE | MEAN | MEAN | DIFF IN MEAN | T-STAT |
| EXP | 16.63 | 8.43 | **8.20*** ** | 13.09 |
| LNBRKSIZE | 3.76 | 4.08 | **-0.32** ** | -3.63 |
| PORTFOLIO | 1.42 | 1.25 | **0.17** ** | 3.57 |
| TOTFIRMS | 11.53 | 8.73 | **2.80*** ** | 5.49 |

***, **, * Denote significance at the 1%, 5%, and 10% levels, respectively.

Panel C – Likelihood of Success as a superstar*

$$STAR = \gamma_0 + \gamma_1 EXP_{i,t} + \gamma_2 BRKSIZE_{i,t} + \gamma_3 PORTFOLIO_{i,t} + \gamma_4 FIRMFOLL_{i,t}$$

| VARIABLE | Coefficient | Odds Ratio | P-Value |
|---|---|---|---|
| INTERCEPT | -4.2734 | | <.0001 |
| EXP | **0.1488*** ** | 1.16 | <.0001 |
| BRKSIZE | **-0.4121*** ** | 0.662 | 0.0024 |
| PORTFOLIO | 0.2384 | 1.269 | 0.2544 |
| TOTFIRMS | 0.0329 | 1.033 | 0.1368 |

$R^2 = 0.190$

Number of observations: 88 Superstars, 2,773 non-stars

**Table 5 Test of Hypothesis 4 – Firm Characteristics**

**Panel A – Correlation Table**

| | ANALYS FOLL | BTM | LNSIZE | BETA | BLKHLD | LNASSTS |
|---|---|---|---|---|---|---|
| ANALYSFOLL | | -0.155<br><.0001 | 0.575<br><.0001 | 0.084<br><.0001 | 0.344<br><.0001 | 0.408<br><.0001 |
| BTM | -0.066<br><.0001 | | -0.278<br><.0001 | 0.100<br><.0001 | -0.086<br><.0001 | 0.095<br><.0001 |
| LNSIZE | 0.581<br><.0001 | -0.133<br><.0001 | | -0.157<br><.0001 | 0.289<br><.0001 | 0.786<br><.0001 |
| BETA | 0.066<br><.0001 | 0.055<br><.0001 | -0.153<br><.0001 | | 0.141<br><.0001 | -0.086<br><.0001 |
| BLKHLD | 0.266<br><.0001 | -0.050<br><.0001 | 0.264<br><.0001 | 0.095<br><.0001 | | 0.080<br><.0001 |
| LNASSTS | 0.425<br><.0001 | 0.023<br>0.001 | 0.789<br><.0001 | -0.050<br><.0001 | 0.050<br><.0001 | |

**Panel B – Test of Difference in means**

| | STARS (N=4,217) | NON-STARS (N=16,873) | | |
|---|---|---|---|---|
| VARIABLE | MEAN | MEAN | DIFF IN MEAN | T-STAT |
| ANALYSFOLL | 9.290 | 5.530 | **3.760** | 40.61 |
| BTM | 0.550 | 0.598 | **-0.048** | -2.73 |
| LNSIZE | 14.650 | 13.650 | **1.000** | 35.85 |
| BETA | 1.242 | 1.212 | **0.030** | 2.30 |
| BLKHLD | 0.772 | 0.658 | **0.114** | 23.22 |
| LNASSETS | 7.978 | 7.111 | **0.867** | 27.37 |

**Panel C – Superstar likelihood to pick a firm**

| VARIABLE | Coefficient | P-Value | Odds Ratio |
|---|---|---|---|
| Intercept | **-5.108** | <.0001 | |
| ANALYSFOLL | **0.078** | <.0001 | 1.081 |
| BTM | 0.030 | 0.259 | 1.030 |
| LNSIZE | **0.216** | <.0001 | 1.241 |
| BETA | **0.098** | 0.021 | 1.103 |
| BLKHLD | **0.823** | <.0001 | 2.277 |
| LNASSETS | -0.059 | 0.016 | 0.942 |

$R^2$ = 0.13. Star Observations = 2,692 and Non-star Observations =7,749

**Table 6 A–Superstar Recommendations**

| YEAR | STRONG BUY | BUY | HOLD | SELL | STRONG SELL | TOTAL RECOMMEN DATIONS | % SELL RECOMMEN DATIONS |
|---|---|---|---|---|---|---|---|
| 2002 | 324 | 488 | 590 | 77 | 16 | 1495 | 6.22% |
| 2003 | 224 | 314 | 532 | 99 | 45 | 1214 | 11.86% |
| 2004 | 183 | 224 | 398 | 65 | 25 | 895 | 10.06% |
| 2005 | 217 | 231 | 456 | 69 | 30 | 1003 | 9.87% |
| 2006 | 182 | 222 | 435 | 60 | 21 | 920 | 8.80% |
| 2007 | 153 | 250 | 413 | 57 | 25 | 898 | 9.13% |
| 2008 | 142 | 242 | 424 | 60 | 24 | 892 | 9.42% |
| 2009 | 153 | 197 | 371 | 72 | 41 | 834 | 13.55% |
| 2010 | 154 | 190 | 312 | 33 | 15 | 704 | 6.82% |

**Table 6 B– Annual Portfolio Returns on Superstars' Recommendations**

| YEAR | UNADJUSTED RETURNS | | MKT ADJUSTED RETURNS | |
|---|---|---|---|---|
| | MEAN | MEDIAN | MEAN | MEDIAN |
| 2002 | 0.4313 | 0.0187 | 1.4237 | 0.4478 |
| 2003 | 1.1664 | 0.2401 | (0.2020) | (0.0240) |
| 2004 | 0.8451 | 0.3365 | 0.4086 | 0.1414 |
| 2005 | 0.9985 | 0.3161 | 0.1573 | 0.1444 |
| 2006 | 1.3652 | 0.1972 | (0.2443) | 0.0119 |
| 2007 | 0.7430 | 0.3975 | 0.1551 | 0.1084 |
| 2008 | 0.1813 | (0.0096) | 1.2430 | 0.2616 |
| 2009 | 0.8716 | 0.4709 | 0.4223 | 0.2790 |
| 2010 | 1.0860 | 0.3074 | 0.0412 | 0.0840 |